Università di Scienze Gastronomiche di Pollenzo
University of Gastronomic Sciences of Pollenzo

Unveiling Consumer Dynamics

Multivariate Analysis Techniques to Navigate Hidden Patterns of Consumption in Transition Times

Maria Giovanna Onorati

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Preface by
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Sapere aude: incipe.

[Horace (*Epistulae*, I, 2, 40), 20 B.C.]

(*Dare to know: begin!*)

Contents

Preface by *F. D. d'Ovidio* .....p. 7

Chapter 1.
The reasons behind observable facts: Consumer patterns under sociological scrutiny ... 11

1.1. Introduction 13

1.2. Delving into Consumer Patterns to Driving the Change and not Undergo to It.....14

1.3. Consumption in the Social Sciences. Definitions and Research Methods 15

Chapter 2.
Introduction to Factor Analysis: Basic concepts to know 21

2.1. Introductory Concepts of Multivariate Analysis 23

2.2. Why Using Factor Analysis in Sociological Analysis of Consumer Culture and Behavior?.....23

2.3. Basic Concepts of Factor Analysis. A Guided Use of Factor Analysis with SPSS (Statistical Package for the Social Sciences).....24

2.3.1. What is Factor Analysis?.....24

2.3.2. What are Factors? 25

2.3.3. What do Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity represent in a Factor Analysis?.....26

2.3.4. What is Iteration in Factor Analysis? 27

2.3.5. How many iterations are recommendable?.....27

2.3.6. Why Rotate the Factor Matrix? 27

2.3.7. What is Varimax Rotation?.....29

2.3.8. Why is the Varimax Method so Popular?.....29

2.3.9. What is communality?.....30

2.3.10. What are Loading Coefficients? 31

2.3.11. How are communality and loading coefficients used in Factor Analysis?....31

2.3.12. What is an Eigenvalue ("Autovalore")? 32

2.3.13. What is a screeplot?.....33

Chapter 3.
Factor analysis to explore evolving consumer patterns ..... p. 35

3.1. Factor analysis to explore antinomies and values driving food-related patterns in a sample of Italian consumers 37

3.2. Preparation of the factorial analysis on SPSS 40

3.3. Step-by-step factor analysis: Let's begin! 41

3.4. Initial Output from the Conducted Factor Analysis 48

3.4.1. Descriptive statistics 48

3.4.2. Tests of Sample Adequacy for Factor Analysis 49

3.4.3. How do these factors distribute among the surveyed population? Do they exhibit variations based on the personal characteristics of respondents? 60

3.4.4. Graphic Visualization of the Extracted Factors 62

Chapter 4.
Cluster analysis to identify consumer groups based on the hidden patterns found 67

4.1. The relevance of cluster analysis in the study of consumer culture and behaviour 69

4.2. What is Cluster Analysis? 69

4.3. Preparation of the K-Means Cluster Analysis on SPSS 71

4.3.1. Identification of the variables to use in Cluster Analysis 71

4.3.2. Settings for implementing Cluster Analysis 72

4.4. Results and Interpretation of the Cluster Analysis 76

4.5. Representing Cluster Distribution Across Sociodemographic and Personal Lifestyle Characteristics 80

4.6. Standardizing variables for Factor Analysis 83

Acknowledgments 87

References 87

Visited Websites 89

Author's Short bio 89

Preface

Professor Emeritus Francesco Delvecchio (born in 1930) was my academic mentor at the University of Bari (Italy). As a person with a deep Catholic conviction and a curious nature, he always held the belief that Mathematics is "the language of God", able of offering universal explanations about the world. This conviction is unsurprising for a scholar who graduated in Mathematical Sciences and started his career as an assistant in the Chair of Rational Mechanics, eventually becoming a professor and researcher in Mathematical Physics. However, despite this steadfast belief, shared by many scholars in his field, he experienced a profound revelation over sixty years ago. On his personal Damascus Road, he discovered something even more intimate in his connection with the divine. This revelation, as he once shared with me, was none other than Social Statistics, a discipline employing mathematical means and tools to delve into the intricacies of human events and vicissitudes. For him, Social Statistics united the Word and the Deed, putting those universal explanations about the world to the test amid the elusive complexity of events in the world. This revelation translated for the mathematician into a new perspective, imbuing the divine language with a poetics of variable and often imperfect geometries, undeniably challenging and fascinating for scientists of any faith, be they believers, agnostics, or atheists.

The first discipline with which Social Statistics 'compromised' is Sociology, the offspring of philosophical positivism. Sociology studies societies and their institutions, along with the relationships between these institutions and the individuals who inhabit them. It explores social interactions among individuals, the products of these relationships, such as culture, and the behaviors and experiences of individuals within social groups. What distinguishes Sociology from other social sciences is its obligation to account for its diverse, inherently human subject matter in supra-individual terms. As sociologists study societies rather than individual persons, even when employing interpretative methods focused on subjectivities or micro-groups, they must be able to generalize their conclusions. To achieve this, they are tasked with collecting and studying, methodically, numerous pieces of information concerning these communities on behalf of which they speak. These study objects constitute "research data", crucial for interpreting social phenomena based on a series of concepts and theories, sometimes *preceding* and sometimes *following* empirical observation. How are concepts and data, theories and observations connected?

While interpretative approaches to empirical observations have yielded numerous insights crucial for sociological imagination, particularly in times of great complexity, quantitative research remains the privileged ally and, to some extent, an indispensable tool for Sociology. The 'scalability of results' is an integral part of its supra-individual vision. Quantitative research spans from simple descriptive analyses of raw data or percentages to inferential efforts of generalization, typically expressed through averages. Alternatively, it can delve into the realm of collective mathematics, Statistics, and particularly Social Statistics, to achieve advanced analyses capable of integrating the multiplicity of dimensions involved in human and social dynamics with the orderly geometry of numbers.

As taught by one of the most distinguished Italian methodologists in social research, Piergiorgio Corbetta (highly esteemed by many social statisticians), Sociology emerges as a multifaceted discipline. Although qualitative and quantitative methods represent radically different research approaches, they are not mutually exclusive but rather complementary. Their intersection can be found in the realm of methodological rigor and its alignment with reference social theories. Applied statistics in social research, offering statistical analysis techniques primarily for qualitative research questions, constitutes a scientific field where the complementarity between depth (typically associated with qualitative methods) and probability (the domain of statistics) converges.

In essence, this manual originates from the author's indirect encounter with the teachings of the two aforementioned scholars. The first encounter took place through me as an intermediary, systematically introducing Professor Onorati to the secrets of Social Statistics. The second encounter occurred through a direct acquaintance with books on social research methodology, including the 'historical' works by Bailey (1978) and Blalock (1979) – cornerstones of the vast scientific branch that unites statisticians and sociologists in an ideal embrace, despite hailing from seemingly distant worlds. After grasping the core principles of statistics, the Author mastered these books to perfection. It is often said that 'appetite comes with eating,' and, similarly, scientific knowledge becomes essential nourishment – food for the mind, especially for sociological imagination.

I met Professor Onorati twenty years ago when she was a young researcher in Sociology of Communication, dedicated (then, as always, it seems to me) to numerous and ambitious projects. At that time, her research was primarily focused on the media consumption of children and preadolescents. She had a distinctly humanistic background, rooted in philosophy and linguistic-communication studies, and everything she knew about quantitative methods she had learned from research methodology books and by attending summer schools in methodology. However, these non-systematic forays into quantitative investigation revealed a unique curve of her pronounced sociological imagination: an interest in the possibility of generalizing research results beyond the scope of her own eyes and observations. For her, this translated into a continuous quest for the robustness, 'scalability,' and verifiability of the explanations for the phenomena under investigation, as well as the coherence and theoretical appropriateness of the research hypotheses. So here unfolds her own Damascus Road, revealing itself to her through me, and, over time, to me through her. During her youth, I recommended to the researcher to progressively complement her excellent humanistic background with the study of quantitative techniques. This guidance empowered her to pose the right research questions, leading to increasingly robust and original results. It was in this period that the encounter between the 'humanistic' sociologist and the social statistician occurred.

Certainly, all of this was facilitated by the fact that the sociologist did not encounter a pure theorist. For such a theorist, even the most basic statistics cannot be compiled without a thorough understanding of probability calculations, the theory of the normal distribution curve, linear correlation, and a hundred other progressively more abstract mathematical concepts. Faced with these, the curiosity of sociological imagination would have stalled and dissolved into a puff of vapor, much like a vial of precious essence dropped into the scorching Sahara Desert.

Instead, we talked about concrete things, such as quantifying questions that were mostly qualitative around common concepts. For example, what certain types of people do in specific contexts and situations of daily life, and how to attempt measuring them with simple calculations. I remember her astonishment and enthusiasm when, after a few of these mostly instructional meetings, she realized what she was achieving with the research data collected up to that point. Quantitative analysis, far from diminishing the depth of the need for qualitative understanding, revealed aspects and explanatory possibilities that were unimaginable with qualitative investigation alone.

Almost without realizing it, acquiring the practice of statistics and continuing to be passionate about the results she obtained, she began to approach the mathematical theory that led to these results. By then, I wasn't teaching her anymore; we had already become collaborators in some of her scientific research. Yet, she was always there, studying the basic mathematical mechanisms, despite the difficulties she might encounter. After all this hands-on training, in a "bottom-up" fashion (from practice to theory), she felt ready to undertake a more classical path in quantitative research, following the guidelines laid out by that methodology manual that had marked - initially as an exploration - her early training. Armed with this new knowledge, and consistently supported by me, Professor Onorati began to engage not only with increasingly innovative social theories but also with statistical techniques and tools she had never imagined adopting in her studies aimed at capturing the "depth" not immediately observable in social phenomena and mastering "reflective" analyses. As evident in her numerous scientific articles, we're talking about techniques such as Principal Component Analysis, Factor Analysis, Cluster Analysis, Multidimensional Scaling, Structural Equation Models — basically, everything that falls under the generic umbrella definition of "multivariate analysis".

And now, we've arrived here.

In this concise and essential manual, only some of the powerful statistical tools that the Author has acquired through experience and determination are presented. The practice and theory are alternated with correctness and passion, a combination that cannot help but make me proud of her scientific journey. This journey in quantitative sociology is generously made available here to students worldwide. I hope they can benefit from the same successful approach to the apparent mathematical complexity of quantitative research, which, while simplifying, never oversimplifies or reduces the interpretation of an increasingly complex society.

The Author provides us with a coherent and highly contemporary analytical pathway, aligning seamlessly with the preceding discussion. It starts with an initial chapter that frames, within a well-defined theoretical and sociological framework, the social phenomenon of the "new normality" and the transition – in the broadest sense of the term – inaugurated first by the COVID-19 pandemic, both in Italy and in much of the world, and then by the numerous crises that have arisen from it. There is a consequent need to delve into consumption patterns (especially food consumption, given the disciplinary focus of the courses, but not only) and the motivations, increasingly elusive and changeable, guiding often contradictory choices.

Following this, Chapter 2 unfolds, presenting readers with one of the most valuable and suitable quantitative techniques for discerning new consumer patterns and behaviors: Factor Analysis. This technique is part of a broader spectrum of multivariate statistical

methods, distinguished by their ability to consider not just one characteristic at a time among those observed, but to simultaneously assess a broad array of characteristics. This approach allows for the discernment of relationships established between different features of individuals or groups. By giving shape to the complex relationships that define real phenomena, these techniques prove instrumental in outlining new consumption models, capturing underlying motivations that drive social actions—often motivations unknown to the actors themselves. The chapter delves into the operational presentation of these analysis techniques, commencing with a description of basic concepts related to Factor Analysis. Special attention is given to the essential understanding of 'extraction' techniques for the factors to be analyzed, including those presented in this book—specifically, Principal Components Analysis (PCA) and Unweighted Least Squares (ULS), with an explanation of when and why to prefer one over the other. This section of the volume guides readers through the step-by-step practical application of Factor Analysis, richly illustrated with examples and graphics showcasing operations conducted using the SPSS software. The choice of SPSS is deliberate, as it is an IBM statistical analysis program tailored for the social sciences. Known for its user-friendly interface, SPSS accommodates users with varying levels of statistical knowledge, making it accessible to both those with minimal expertise and those with advanced skills, depending on the researcher's skills.

Chapter 3 delves into a comprehensive exploration, enriching the depth and breadth of results and interpretations achievable through additional steps aimed at validating and applying the outputs of Factor Analysis. This includes tools to ensure the internal consistency of scales constituting factors, as well as to identify statistical significance between factors and the personal characteristics of the surveyed population.

The final section of this essential manual, Chapter 4, introduces us to another multivariate technique often used in conjunction with Factor Analysis in the social study of consumption and marketing: Cluster Analysis. This technique is based on multivariate relationships, but this time expressed not between variables (characteristics of the objects studied) but between statistical units (the subjects themselves) based on their own characteristics. These relationships are similarities or dissimilarities (defined as "distances").

These are just some of the many techniques that Statistics provides for Quantitative Social Research. Those who learn to master these essential and now widely used techniques, as the author proposes, can over time embark on an important and fruitful journey through the Mediterranean Sea of sociological knowledge, extend beyond the reach of their gaze, and one day even venture into the Ocean to discover new continents.

Bari, January 20, 2024

Francesco D. d'Ovidio

Professor of Social Statistics,
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Chapter 1.

The reasons behind observable facts: Consumer patterns under sociological scrutiny

1.1. Introduction

Since January 2020, amidst a pandemic that has transformed into a 'new normal' coexistence with a partially tamed but still unfamiliar virus, economic instability characterized by unpredictable fluctuations, and escalating political unrest, the world has plunged into a phase of a 'multifaceted crisis' that shows no signs of abating. The prolonged period of instability and insecurity, defined as the 'permacrisis,' was named the word of the year for 2022 according to Collins Dictionary [1].

The many facets of the crisis morphed into various forms of upheaval, labeled as 'emergency' (health-), 'disaster' (climate-), 'catastrophe' (humanitarian), and 'shock' (energy), etc., leading to significant shifts in consumer patterns. The widespread integration of new artificial intelligence has evoked contradictory sentiments, leaving the majority of consumers feeling overwhelmed and distracted. These shifts accelerated a transition that before was just on the paper or on the agenda. At times, these shifts have been accelerations, such as the ecological transition or technological digitization in consumption, work, and education. Other times, they have involved steering with changes of direction, like returning to produce what was no longer produced simply because it was imported. In some cases, the turn has resulted in steps backward, such as the distrust toward the global dimension.

These shifts often result in contradictory behaviors that require identification, as well as emerging trends that should be addressed (Campbell et al. 2020). Global market insights have diligently pinpointed and characterized these frequently conflicting trends, some of which have the potential to act as pivotal moments steering towards enduring alternatives. According to Mintel, ongoing trends that are particularly noteworthy for brands to consider encompass a fresh sense of 'being human,' a non-materialistic aspiration for acquiring 'more than money,' a renaissance of 'relationships' following an extended period of social separation and home confinement, and an internalized 'new green awareness,' harmonizing with an overarching sense of 'positive perspectives' (Mintel, 2024). On the other hand, Euromonitor adopts a more cautious stance, emphasizing the role of AI in propelling the human-machine ecosystem toward co-creation, influencing consumers' daily lives and decisions, and noting a progressively polarized demand for stance-taking. This escalation of tensions occurs despite the increasing desire for relief from anxiety and an opportunity to break away from mundane stressors (Euromonitor, 2024).

During periods of profound social change, when the predictive capabilities of expert systems weaken or falter and perspectives become limited, the ability to understand not only what consumers want and why, but also to monitor their actions and potential actions becomes crucial in facilitating the alignment of supply with demand. According to one of the main global market analysists, still today, consumers around the world provide evidence they want to connect with brands and,

> […] brands must reestablish and strengthen their relationship with consumers, placing consistent delivery of functionality at the core of their message and ensuring that reliability, trust and authenticity feed into the integrity of their identity and vision (Mintel, 2024).

[1] See: https://blog.collinsdictionary.com/language-lovers/a-year-of-permacrisis/

Italy, alongside numerous European nations, has experienced a sequence of sudden changes and disruptive shifts in daily behaviors and routines. After experiencing robust economic growth in 2021 and 2022, resulting from attitudes to "revenge consumption" as pandemic-related restrictions are lifted and savings accumulated during confinement periods, the Italian economy is now grappling with a decline in consumption owing to persistent inflation. Consumers lost purchase power, bank deposits start decreasing for the first time in 11 years and the use of consumer credit is on the rise (Nomisma, 2023). Inflation, which began to decrease in 2023, has not yet receded from the 8% mark on essential grocery items, leading people to reconsider their traditional Italian foodways. Nevertheless, even though the food basket shrinks, buying fresh food remains a top concern for Italian consumers. Moreover, in an overall review of grocery shopping, local food has taken precedence over organic options, confirming a willingness to spend more for concerns that have become inescapable claims by consumers.

1.2. Delving into Consumer Patterns to Driving the Change and not Undergo to It

Delving into consumer patterns entails a reflexive approach to shifting trends in the market, enabling the capture of often conflicting drivers and values lying behind consumption behaviors, even when these seem to seamlessly converge towards desirable goals. Moreover, understanding and exploring consumer patterns allows both marketers and scholars to actively influence or lead change rather than being passively subjected to it. This is a strategic goal for both social science and marketing.

Scholars, particularly sociologists and experts in consumption and social change, may argue that attention to what consumers want depends on the specific theory of consumption or social change employed (Halkier, 2017). However, irrespective of the theoretical framework in use, the recognition of citizens and consumers as knowledgeable and capable actors remains of paramount significance during periods of transition. This acknowledgment holds true particularly in the presence of theories and methodologies aiming to provide a comprehensive and systemic understanding of the phenomena under investigation. Especially during crises, marked by multiple disruptive events such as a pandemic outbreak, energy shocks, rising inflation, raw material shortages, and climate change disasters, which serve as dramatic accelerators of social change, the role of human agency in transition processes and shifting axiologies should be consistently considered (Onorati & d'Ovidio, 2022). This is because citizens and consumers are the 'change agents' propelling change forward (Spaargaren *et al.*, 2006). Striking a balance between socially organized shifting routines and reflexive actor, often deemed as irreducible as chalk and cheese (Shove, 2011) is crucial, both in terms of the theoretical framework and the methodology employed. This is necessary to sidestep "individualistic explanations" of behavioral change, a common pitfall associated with psycho-social perspectives (Warde, 2014).

Equally important is not to overlook the role of human agency and individual value-based interpretation of changing behaviors, contrarily to recent formulations of practice theoretical approaches, as the one suggested by Huddart Kennedy (2023), which emphasizes dismissing values in her analysis of social change. If, on the one side, the

emphasis on individual's motives, values, and beliefs is too strong within the social psychological paradigm, suggesting that individual motivation is the sole means to achieve a transition to sustainability, downplaying the influence of social (including technological) structures on behavior; on the other side, reducing individuals to mere participants in routines as practice-theoretical approaches suggest, effacing whatever personal value-based sense-making of changing behaviours, risks to disregard the axiological background that normate practices. Giving up to values (Huddart Kennedy, 2022) and substituting them through interests as significant factors shaping praxis, while beneficial for examining how relationships are enacted within specific contexts, carries the risk of introducing excessive variability into the phenomena under scrutiny. Such skipping axiology, in turn, may hinder the analysis from capturing the broader and more comprehensive dynamics of change.

1.3. Consumption in the Social Sciences. Definitions and Research Methods

As noted by Aldridge in 2003, 'consumption' is considered a 'key concept' in the social sciences as it 'unlocks the way' to new domains and offers insights into our relationship with various goods and services. The importance of this concept arises from the fact that consumption extends well beyond the act of purchasing.

According to the comprehensive definition provided by Campbell (1995), 'consumption' involves the selection, purchase, use, maintenance, repair, and disposal of any given product or service. 'Consumption' alludes to a sequence of activities inextricably tied to the product as much as to the 'consumer'—two terms that shape our understanding of consumption as a relationship. Because of the far-reaching implications of this notion, consumption is an inherently interdisciplinary concept.

According to Halkier (2017), there are four distinct analytical 'families' considered as the primary groupings for researching consumption in the social and cultural sciences. In empirical research, it's important that methodological assumptions align with the chosen theoretical perspective.

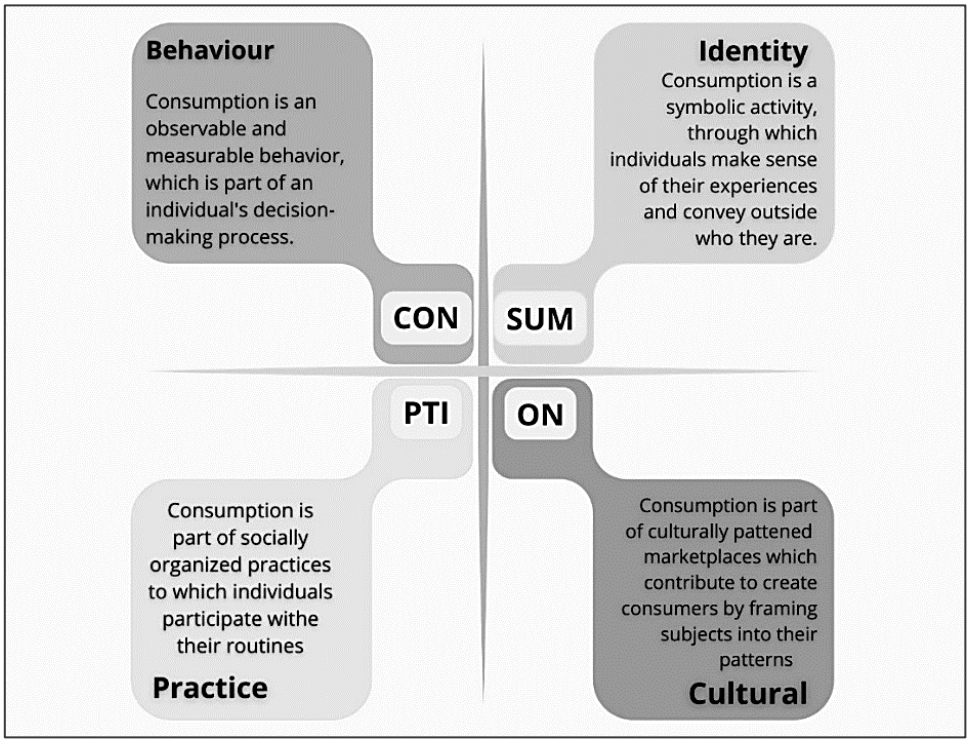
What makes consumption an authentically transdisciplinary field of study is its intersection of the following four characteristics:

- **The importance of macro-contexts**, such as economic, socio-economic, and structural dynamics that can have a patterning influence on individual behaviors (consumption as behavior).
- **The importance of micro-contexts**, involving communicative interpersonal dynamics through which individuals can discursively generate their identity (subjects primarily act as symbolic subjects).
- **The importance of meso-contexts**, encompassing specific settings (formal, informal, institutional, etc.) with which individuals interact as social actors, contributing to both subjective and objective formation (subjects and contexts interact).
- **The importance of organized daily-life contexts** (meso- and micro-), including specific settings (formal, informal, institutional, etc.) where individuals engage in

habitual activities, contributing to their reproduction and slightly to their change (subjects are mainly participants in socially organized routines).

From a sociological perspective, consumption encompasses all four dimensions suggested by Halkier, and they can be schematized as in Fig. 1.

Figure 1. *The four 'families' considered as the primary groupings for researching consumption*


Behaviour
Consumption is an observable and measurable behavior, which is part of an individual's decision-making process.
Identity
Consumption is a symbolic activity, through which individuals make sense of their experiences and convey outside who they are.
CON
SUM
PTI
ON
Consumption is part of socially organized practices to which individuals participate withe their routines
Practice
Consumption is part of culturally pattened marketplaces which contribute to create consumers by framing subjects into their patterns
Cultural

The four broad categories of consumption research around which research methods and discussions are organized follow Halkier's classification (2017) and can be described as follows:

1. **Consumption as behavior:** This definition is predominantly emphasized in disciplines such as economics, psychology, social psychology, and sociology, particularly when applied to marketing. Consumption is viewed an observable and measurable behavior, which is part of an individual's decision-making process. The *epistemological approach* is grounded in the positivistic logic of discovery through systematic observation of manifest phenomena. Typically, *research questions* aim to understand the motives behind patterns of habits, posing inquiries such as: 'How important is it for you?' or 'How likely are you to use, to buy, to eat...?' The *unit of analysis* is the individual, focusing on measurable patterns of behaviors (habits) considered as phenomenic variations of basic invariant patterns, making them measurable and comparable. The *research approach* is quantitative, involving statistical modeling of self-reported behaviors, often combined with direct observation when testing is the objective. *Research tools* commonly include surveys, often complemented with focus groups.
2. **Consumption as identity:** this definition is predominantly prioritized by disciplines such as cultural sociology, semiotics, communication studies and social anthropology.

Consumption is viewed as a symbolic activity through which individuals make sense of their experiences and communicate their identity to the outside world. In this case, this approach is relevant for marketing to identify consumer targets. The *epistemological approach* is rooted in narrative subjectivism and interpretative intersubjectivism, where communication and language play central roles. *Research questions* typically aim to understand the types of consumer experiences and how consumers make sense of their own and others' consumption. The *unit of analysis* is symbolic/communicative individuals intersubjectively embedded in communicative contexts. The *research approach* is primarily qualitative, relying on consumer discursive/narrative expression, but it can also include quantitative methods applied to text analysis. Common *research tools* include individual narrative interviews, focus groups, and text analysis.

3. **Consumption as cultural dynamics:** this definition is predominantly emphasized in disciplines such as cultural sociology, social psychology, and social anthropology of a constructivist matrix. Consumption is perceived as part of culturally patterned marketplaces that contribute to creating consumers by framing subjects into their patterns. The *epistemological approach* is grounded in social constructivism and critical realism. *Research questions* typically aim to understand marketplace cultures, socio-historic patterning of consumption, and the meeting of marketplace discourses and consumer sense-making. They pose inquiries such as: 'What characterizes the cultural context of consumption?' 'How are consumer subject positions discursively produced?' and 'How have specific consumption patterns developed historically?' The *unit of analysis* involves intersubjectively created cultural patterns based on the interaction between communicative subjects and cultural contexts. The *research approach* is predominantly qualitative, namely ethnographic situationism and semiotic interactionism. Common *research tools* include non-intrusive participant observation, active interviewing, and text/discourse analysis reported through qualitative surveys.

4. **Consumption as a component of social configurations:** this definition is predominantly emphasized in disciplines such as sociology, with moderate consideration for socio-cultural approaches. In this definition, consumption is perceived as a part of socially organized practices in which individuals actively participate and reproduce through their routines. The *epistemological approach* is grounded in practice theory, advocating for an anti-individualistic perspective, with a focus on inconspicuous forms of consumption. *Research questions* typically aim to understand the temporal and spatial organization of ordinary activities, often carried out unreflectively, and how they become integrated into routines. They inquire into aspects such as: 'How is the context of particular types of consumption socially and spatially organized?' 'How are patterns of consumption scheduled?' 'How are object uses embodied in routines?' 'How do individuals participate in routines?' and 'How do consumption patterns become socially, spatially, and materially reproduced and changed?' The *unit of analysis* is the social practice, encompassing routine activities as part of social configurations, which involve organized settings with other people, where the main focus is not on agents but on actions and their objects. The *research approach* is predominantly qualitative, particularly ethnographic, although quantitative analyses are also admitted, such as structural data and digital tracking. Common *research tools* include participant observation, qualitative interviewing, as

well as quantitative surveys, time use analysis (specially to capture social change), and digital data.

Regardless of the particular epistemological approach and methods employed, sociological analysis, even when delving into cultural dynamics, must maintain coherence and congruence with established facts. When Durkheim outlined the principles of the sociological method, revealing his affiliation with positivistic sensibilities, he emphasized the explanatory nature of sociology and its adherence to 'facts,' even when dealing with inherently cultural phenomena, such as religious forms. He identified this explanatory function as a distinguishing feature from other social sciences that study culture. In his own words:

> I will make every effort to describe the organization of this system with all the care and precision that an ethnographer or a historian would bring to the task. But my task will not stop at description. Sociology sets itself different problems from those of history or ethnography. It does not seek to become acquainted with bygone forms of civilization for the sole purpose of being acquainted with and reconstructing them. Instead, like any positive science, its purpose above all is to explain a present reality that is near to us and thus capable of affecting our ideas and actions. That reality is man. More especially, it is present-day man, for there is none other that we have a greater interest in knowing well. Therefore, my study of a very archaic religion will not be for the sheer pleasure of recounting the bizarre and the eccentric. I have made a very archaic religion the subject of my research because it seems better suited than any other to help us comprehend the religious nature of man, that is, to reveal a fundamental and permanent aspect of humanity (Durkheim, 1995 [1912]: 1).

Throughout the first half of the twentieth century, positivistic orthodoxy and its ontological realism—believing 'the world exists independently of our awareness of it'—undergo a process of revision and adjustment in response to the increasing complexity of the social world. This transformation is attributed to the work of many scholars, including Pareto (1935 [1916]) and, later on, Lazarsfeld (1948), a key figure in neopositivist empirical methodology in social research. However, a turning point in sociological perspective is marked by Max Weber, who introduces the interpretative function of sociological explanation, adding a new paradigm in modern sociology. He initiates a significant shift from deterministic to understanding explanations by highlighting the researcher's skill in navigating the complex realm of subjective meanings influencing the social actions under scrutiny. Weber posits the 'existence of a (specifiable) objective possibility' as a guiding principle for social action, elevating it to a factor of 'adequate causation' (Weber, 1949: 164 and ff.).

Far from being a mysterious intuition, sociological 'interpretation' is the endeavor for a rational understanding of the purpose of the action and grasping the motivational chain prompting human behavior (Corbetta, 2003). At least in the Weberian formulation, interpretation, while introducing individuality as a social phenomenon in itself, does not forsake objectivity. Instead of adhering to deterministic laws favored by positivists, sociological understanding seeks causal connections, or, to use Boudon’s expressions, 'mere possibilities' or 'opportunity structures' ('If A, then most frequently B', Boudon, 1984: 75). This implies that interpretation is not in opposition to probability; rather, they are allies (Strand and Lizardo, 2022), where probability is inferentially derived as a

rational interpretation of the 'causal factors' guiding social action (Weber, 1949: 187). Rather than relying on empiricism, sociological interpretation pursues objectivity through abstraction and favors a theory that, among all intrinsically coherent ones, aligns best with the facts.

Whether employing a deterministic framework that articulates regularities in the social world through depersonalized 'language of variables' and causal models (as seen in the neo-positivistic approach by Lazarsfeld and Rosenberg, 1955: 2, 11) or adopting a more interpretative stance through 'ampliative induction' to reconstruct motives not readily accessible through direct fact-checking (as advocated by Boudon, 1984: 31, 51), sociology fundamentally seeks to unveil the invisible reasons underlying social phenomena, which inevitably result from individual actions. In essence, the core objective of social sciences lies in providing an objective account of phenomena that elude direct observation, often termed latent variables or, more colloquially, 'factors'. Particularly sociologists, not unlike psychologists, are tasked with unraveling the plausible connections that link the actions of social subjects to hidden or underlying causes, whether the unit of analysis is an individual or a collective entity. *Although these 'reasons' are entities not directly observable, this does not condemn the sociologist to arbitrariness*.

The overall thrust of advanced research, especially in the realm of social sciences, is explanatory, aiming to provide insights into observed phenomena, problems, or behaviors. In contrast to descriptive research, which focuses on the what, where, and when, explanatory research delves into the why and how, seeking to address questions about causation. Its objective is to establish connections by identifying the factors that cause or influence the target phenomenon and the resulting outcomes.

Multivariate techniques enable us to communicate in the observational language of variables, rooted in operationalization, quantification, and generalization. This approach combines rational quantification with the reflective purpose of capturing the complexity and intricate web of underlying dimensions, value-based, and subjective motivations. While reflective insights are often seen as the exclusive privilege of qualitative research, multivariate techniques transform them from obscure intricate chaos into intelligible, consistent patterns. Multivariate techniques, as outlined by Hair et al. (2019), are employed to analyze multiple variables within a single relationship or set of relationships. They serve to mitigate arbitrariness in reconstructing explanatory relationships between observed behaviors or declared beliefs and an array of underlying factors that can reasonably be identified as causes. The complexity of causative factors inherent in social phenomena underscores the widespread use of multivariate analysis in social research, particularly during the exploratory stages. The 'plausibility' of the identified latent factors is determined by the interplay of theory, research method, and the statistically based evidence available within the data.

This technique heavily relies on statistical evidence of correlations and is employed in extensive quantitative analyses, even when the original questions and research contexts were qualitative or when qualitative questions have been transformed into quantitative data (e.g. Likert scales). Multivariate analysis can be applied to surveys exploring consumption as behavior and social configurations, as well as to voluminous text analysis collected through interviews or captured from digital environments, aiming to investigate cultural dynamics or consumer identity. Statistical techniques that allow us to delve into

the hidden patterns of values driving consumer dietary choices, often aligned with lifestyles, and cluster scrutinized populations according to these hidden dynamics, can be very useful in identifying consumer segments distinguished by different cultural claims in the shifting post-subcultural universe of consumption (Bennett, 2015).

Rather than serving as a conventional handbook on the methodology of social research, this book aims to offer practical guidance for conducting in-depth explanatory research in the field of consumer analysis. In an era marked by transitions, where the datafication of consumer behaviors remains crucial for understanding market trends and registering shifts, consumer analysis must also integrate reflective exploration into beliefs, meanings, and values. This integration is not to be viewed as a separate element of research but as a complementary aspect to enrich insights. This implies not limiting reflective investigation solely to 'qualitative' research but integrating quantitative inquiry with 'reflective' approaches. These approaches reveal hidden patterns that underlie or drive subjective action, even enabling the identification of these patterns as 'typical' features of specific groups or sub-groups. Multivariate analysis, especially the techniques presented in this book, plays a crucial role in achieving this integration.

Chapter 2.

Introduction to Factor Analysis: Basic concepts to know

2.1. Introductory Concepts of Multivariate Analysis

Multivariate analysis is a statistical technique used to analyze data sets with multiple variables. Its aim is to understand the relationships, correlation patterns, and dependencies among these variables collectively, rather than in isolation (as in typical bivariate analysis). Its peculiarity lies in its ability to link numerous observed phenomena with equally numerous causes. It can be applied to both quantitative research, typically involving data collected through surveys submitted to an extensive number of subjects, and qualitative research, which often involves textual data collected through interviews, digital content created by users, and so on. Multivariate analysis encompasses a wide range of techniques, including Factor Analysis, Principal Component Analysis, Cluster Analysis, Multiple Correspondence Analysis, Decision Trees, etc.

Multivariate techniques are often used in combination with each other. Indeed, the flexibility to combine two or more types of analyzes conducted sequentially to gain deeper understanding or insights into a particular research question or problem is very valuable. In the marketing context, utilizing two or more multivariate analysis techniques to delve into consumer insights and make decisions on how to target them often involves combining *Factor Analysis* with *Cluster Analysis* (or *Principal Component Analysis* with *Cluster Analysis*). This integrated approach, specifically proposed by this book, aims to achieve a more comprehensive understanding of evolving customer segments and behavior.

2.2. Why Using Factor Analysis in Sociological Analysis of Consumer Culture and Behavior?

Factor analysis is a multivariate, exploratory technique in data analysis that holds immense importance in market research due to its reflective approach. This method enables a profound understanding of consumer behaviors, uncovering hidden drivers (i.e. 'latent variables') that may be influencing observed behaviors. In essence, factor analysis reduces the multitude of observed variables to a smaller set of common factors, each representing a distinct aspect of the phenomenon under study. These factors have the capability to elucidate a significant portion of the variance in the original observed behaviors.

The objective of employing factor analysis, particularly in marketing and consumer analysis within the realm of social analysis, is to utilize these factors as representations of concealed patterns of consumption. These patterns, in turn, provide insights into the drivers behind observed consumer behaviors and declared preferences, shedding light on the reasons why people behave the way they do. Marketers use this technique to uncover deeper insights into why consumers behave in one way instead of another. Tandem techniques are especially useful during transition periods when predictability is weak or lost, enabling more effective marketing strategies. In this context, we will only consider Factor Analysis and Cluster Analysis, as both are particularly useful for identifying hidden explanatory patterns of observed consumer behaviors and aggregating the surveyed population into segments based on their observed patterns of consumption.

Factor Analysis is employed to identify latent factors underlying observed variables in marketing, such as customer preferences, purchase behaviors, or other data related to customer interactions. On the other hand, Cluster Analysis is used to segment customers

into distinct groups based on similarities, helping marketers identify homogeneous customer groups with similar characteristics or behaviors. Tandem analysis, achieved by combining Factor Analysis and Cluster Analysis, allows marketers to gain insights into the underlying factors that drive customer behavior. Subsequently, Cluster Analysis can further segment customers based on these factors, facilitating a more nuanced understanding of different customer segments.

In the following sections of this book the multivariate techniques will be shown through the use of the software SPSS (Statistical Package for the Social Sciences). This choice is not uncommon among handbooks addressing statistics for social sciences, as demonstrated by the well-known handbook written by Field fifteen years ago, which invited readers to 'discover statistics using SPSS' (…and sex, drugs, and rock'n'roll!). The author justified the selection of this software as follows:

> …in factor analysis we take a lot of information (variables) and SPSS effortlessly reduces this mass of confusion to a simple message (fewer variables) that is easier to digest (Field, 2009: 628).

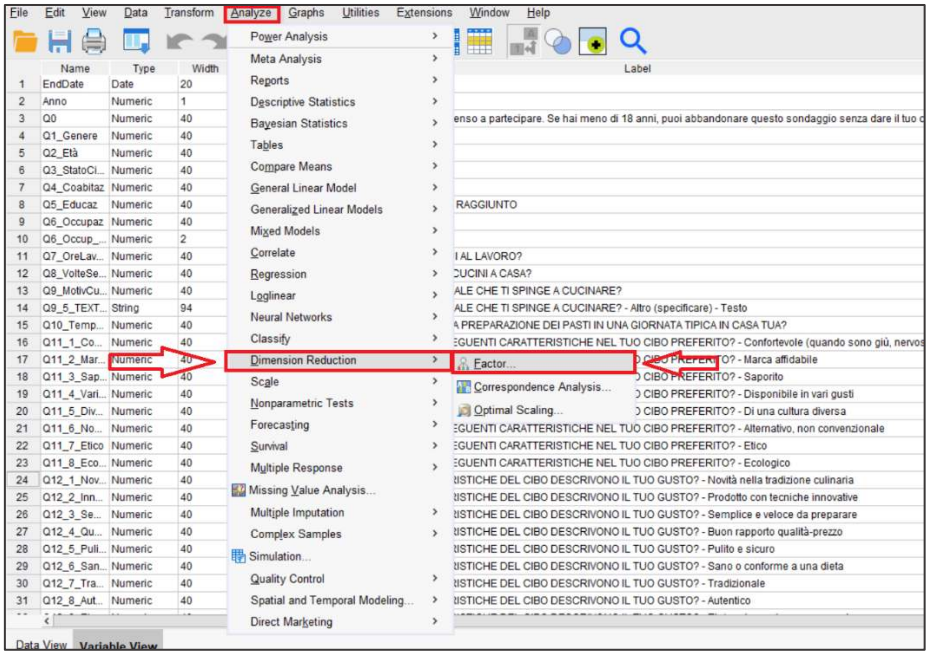
There's no doubt that, even today, SPSS distinguishes itself with its user-friendly and intuitive interface, particularly catering to users with a background in Statistics or social sciences. It provides a graphical user interface that allows users to perform statistical analysis without the need for programming skills.

2.3. Basic Concepts of Factor Analysis. A Guided Use of Factor Analysis with SPSS (Statistical Package for the Social Sciences).

2.2.1. What is Factor Analysis?

Factor Analysis is a multivariate technique employed to streamline the complexity of data. Its main objective is to diminish the number of variables in a dataset as evidenced by its location in the SPSS interface under the option "reduction of dimensions" (Fig. 2).

Figure 2. *Location of "Factor Analysis" in the SPSS interface.*

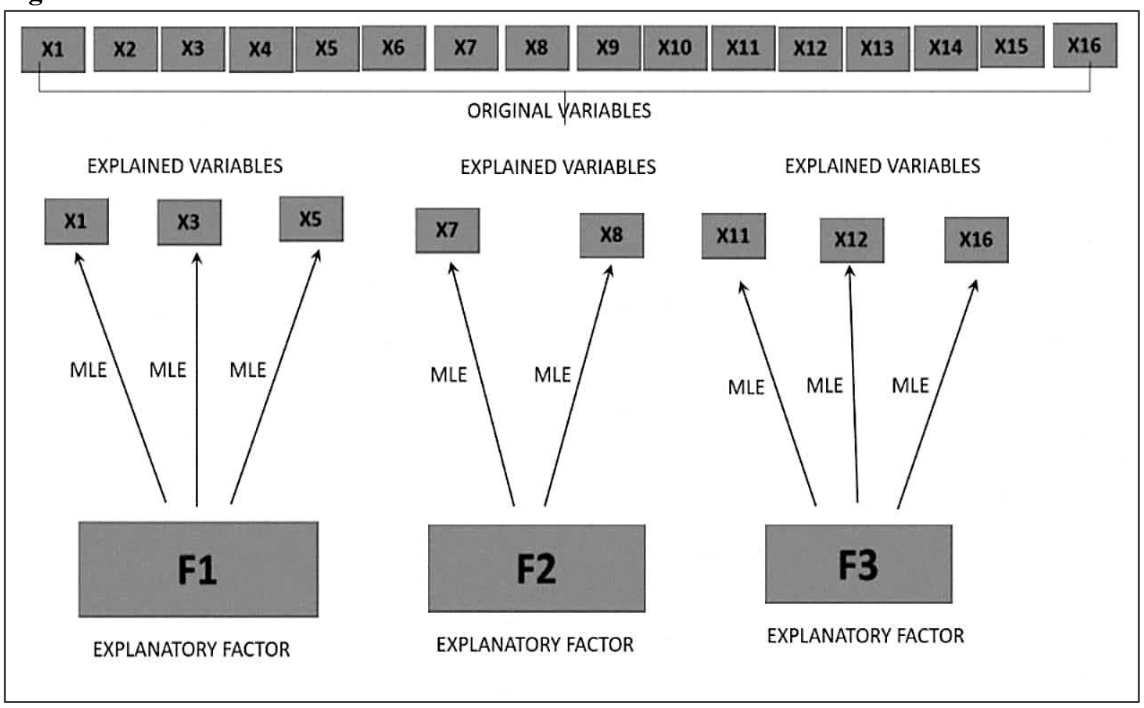


Factor Analysis unveils an underlying factor structure that clarifies the patterns of correlations or covariations among a set of observed variables. Factors, serving as a foundational framework, are typically fewer in number than the original variables in the dataset but can effectively capture a significant portion of the variance within it.

2.3.2. What are Factors?

Factors are based on linear combinations of the observed variables[2], representing underlying dimensions or constructs that explain observed data patterns. They serve as synthetic 'explanations' for the variables in the questionnaire. Factors can be interpreted as latent variables correlated with some observed variables, influencing their manifest variability (Fig. 3).

Figure 3 - *Factors as latent variables correlated with some observed variables.*

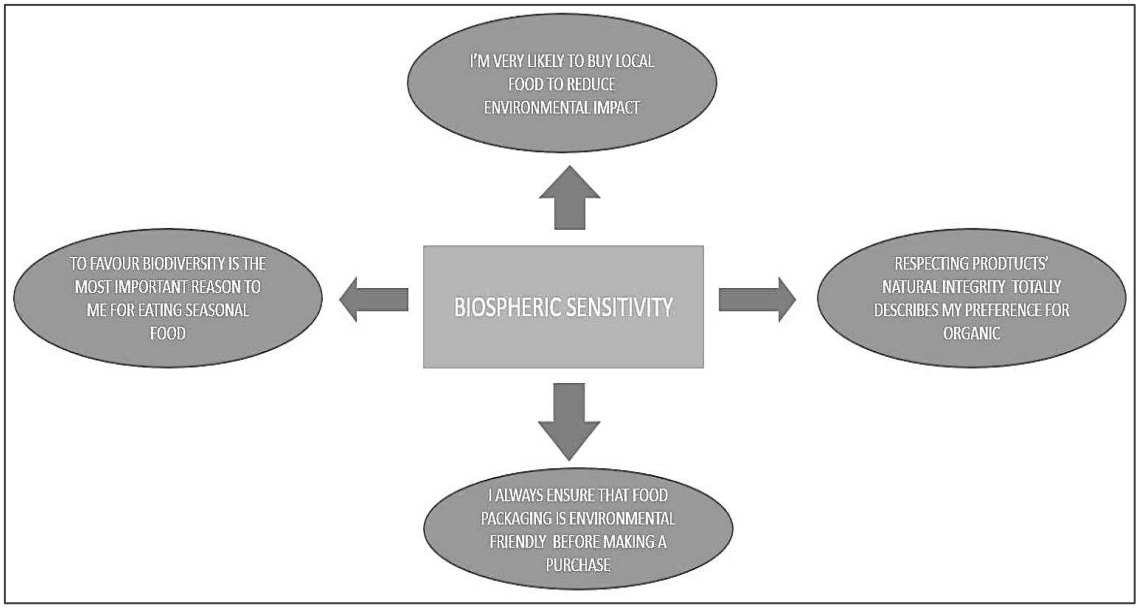


The correlation pattern between the original variables and the extracted factors is primarily determined using Maximum Likelihood Estimation (MLE). MLE is a statistical method employed to find parameter values of covariance that maximize the likelihood of observing the given data (original variables) under the assumed model (the extracted factor structure)

Due to this explorative and explanatory role, Factor Analysis is considered a reflexive technique, particularly suited to sociological needs in understanding underlying characteristics not directly measurable but assumed to be related to observed variables. In essence, within consumer studies, factors represent profound motivations, unconscious cultural patterns, sensitivity, or values that drive consumer actions, decisions, beliefs, and opinions (Fig. 4).

[2] The relationships between factors and original variables can be linear or quite close to linear, depending on the extraction technique and rotation method used. Sometimes, these relationships may be not linear at all, and this flexibility can be useful in understanding complex models.

Figure 4. *Example of reflexive explanatory capability of Factor Analysis.*


I'M VERY LIKELY TO BUY LOCAL FOOD TO REDUCE ENVIRONMENTAL IMPACT
TO FAVOUR BIODIVERSITY IS THE MOST IMPORTANT REASON TO ME FOR EATING SEASONAL FOOD
BIOSPHERIC SENSITIVITY
RESPECTING PRODTUCTS' NATURAL INTEGRITY TOTALLY DESCRIBES MY PREFERENCE FOR ORGANIC
I ALWAYS ENSURE THAT FOOD PACKAGING IS ENVIRONMENTAL FRIENDLY BEFORE MAKING A PURCHASE

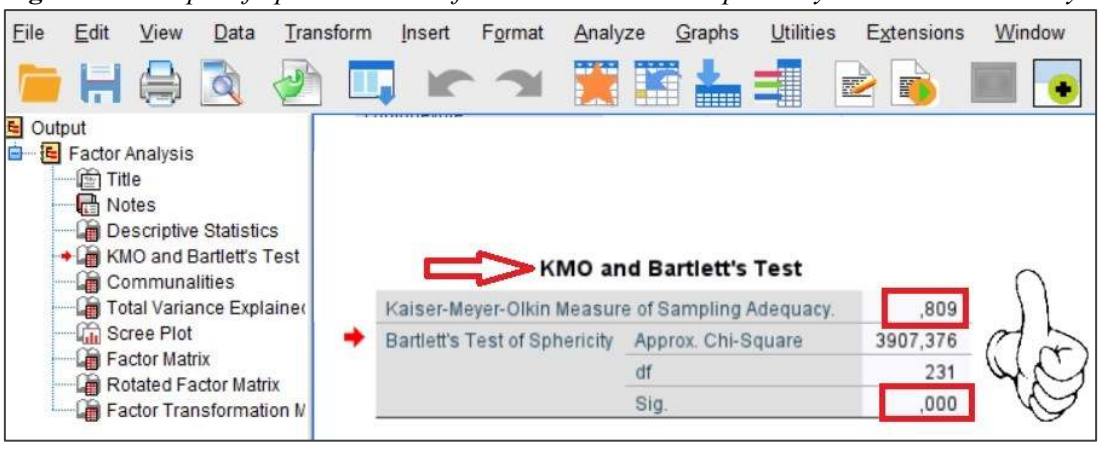
In this context, we will employ Exploratory Factor Analysis (EFA), a technique designed to uncover potential hidden correlations among the observed original variables.

As the term implies, Exploratory Factor Analysis is used when researchers do not have a pre-existing hypothesis to test regarding possible concealed relationships among variables. It serves as an investigative process, helping researchers understand whether associations exist between initial variables and, if so, where they are located and how they are grouped, revealing potential patterns of relations. Despite the exploratory nature of Factor Analysis, theory can aid researchers in interpreting the meaning and evaluating the plausibility and relevance of emerging patterns of relations. Therefore, it is within the researcher's discretion to determine the most suitable factor structure, including the number of factors, based on research goals.

2.3.3. What do Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity represent in a Factor Analysis?

Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity are two statistical measures used to assess the appropriateness of conducting Factor Analysis on a set of variables and to evaluate the quality of the data for this purpose (Fig. 5).

Figure 5. *Example of optimal values of KMO and Bartlett's sphericity tests in Factor Analysis*



The Kaiser-Meyer-Olkin (KMO) measure evaluates the overall adequacy of the data for Factor Analysis by assessing the degree of intercorrelation among the variables. KMO values, which range from 0 to 1 like other correlation parameters, typically closer to 1 (i.e., > 0.6) suggest high correlation among variables, making Factor Analysis an appropriate method. Conversely, a KMO value closer to 0 (i.e., < 0.6) indicates relatively low correlation, making Factor Analysis less suitable.

Bartlett's Sphericity Test examines whether the observed variables significantly correlate with each other. The null hypothesis, positing that variables in the matrix are uncorrelated, has zero probability and can be rejected.

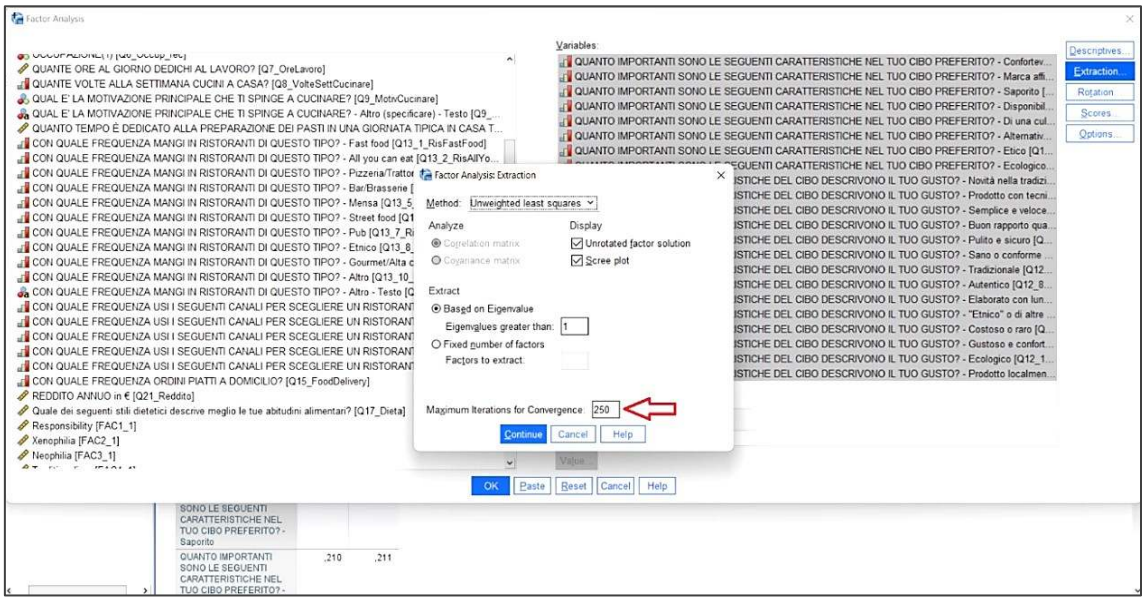
2.3.4. What is Iteration in Factor Analysis?

Factor Analysis is an iterative procedure that aims to converge on a stable solution representing the underlying factor structure of the data. Iterations in Factor Analysis involve repetitive computations, adjusting parameters to refine the model until a satisfactory solution is reached. Convergence criteria determine when the iterative process stops.

2.3.5. How many iterations are recommendable?

The number of iterations in Factor Analysis depends on achieving convergence, and there isn't a fixed recommendation applicable to all analyses. Iterations continue until the algorithm converges on a solution, indicating a fitting factor structure. To prevent premature termination of iterations before convergence, it can be beneficial to consider increasing the default number of iterations in SPSS, which is 25, by adding a zero (Fig. 6). This ensures the algorithm has an adequate opportunity to reach a stable solution.

Figure 6: *Adding a Zero to Default Iterations.*



2.3.6. Why rotate the Factor Matrix?

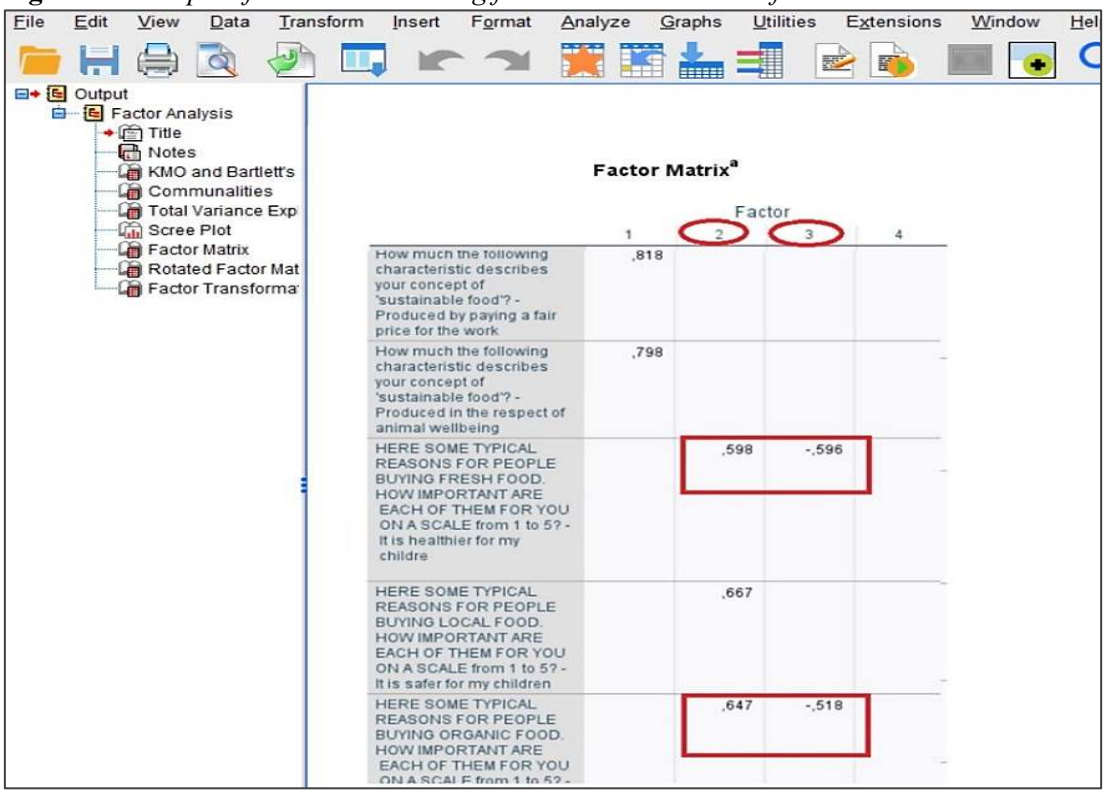
After the factors are extracted, they often exhibit correlation with each other. Variables may load similarly on two or more factors, contributing to the explanation of those factors, as in Fig. 6, where the variables highlighted in red load equally, though with

inverted directions, on Factors 3 and 4. This correlation prevents factors from being perfectly orthogonal. Orthogonality, achieved when factors are uncorrelated and separate, contrasts with the correlated nature of factors in this scenario. The result is overlapping factors, making them non-distinguishable and interpretation challenging.

Factor rotation is a technique employed to reorient the axes in the factor space and achieve the highest possible degree of orthogonality, aiming to simplify and enhance interpretability. This process makes factors more recognizable and distinct.

In the absence of rotation, a factor matrix may exhibit non-distinguishable relationships, as seen in Figure 7. Here, it is evident how a variable contributes similarly to both factor 1 and factor 3, suggesting a correlation between the two factors and making them challenging to differentiate.

Figure 7. *Example of Correlation among factors in the absence of rotation.*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Notes
KMO and Bartlett's
Communalities
Total Variance Exp
Scree Plot
Factor Matrix
Rotated Factor Mat
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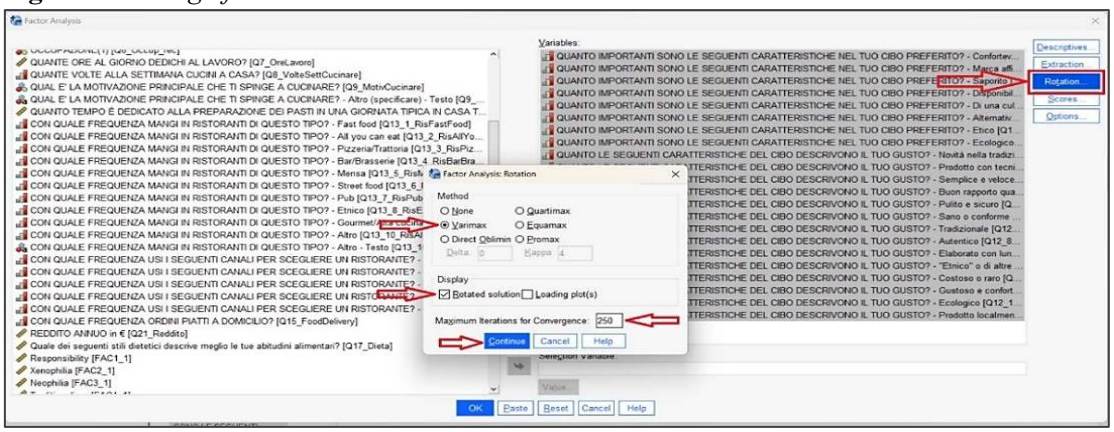
Factor Matrix[a]
Factor
1 2 3 4
How much the following characteristic describes your concept of 'sustainable food'? - Produced by paying a fair price for the work ,818
How much the following characteristic describes your concept of 'sustainable food'? - Produced in the respect of animal wellbeing ,798
HERE SOME TYPICAL REASONS FOR PEOPLE BUYING FRESH FOOD. HOW IMPORTANT ARE EACH OF THEM FOR YOU ON A SCALE from 1 to 5? - It is healthier for my childre ,598 -,596
HERE SOME TYPICAL REASONS FOR PEOPLE BUYING LOCAL FOOD. HOW IMPORTANT ARE EACH OF THEM FOR YOU ON A SCALE from 1 to 5? - It is safer for my children ,667
HERE SOME TYPICAL REASONS FOR PEOPLE BUYING ORGANIC FOOD. HOW IMPORTANT ARE EACH OF THEM FOR YOU ON A SCALE from 1 to 5? - ,647 -,518

Therefore, in our specific context, we choose to apply Varimax rotation (Fig. 8).

Figure 8. *Setting of Varimax Rotation*



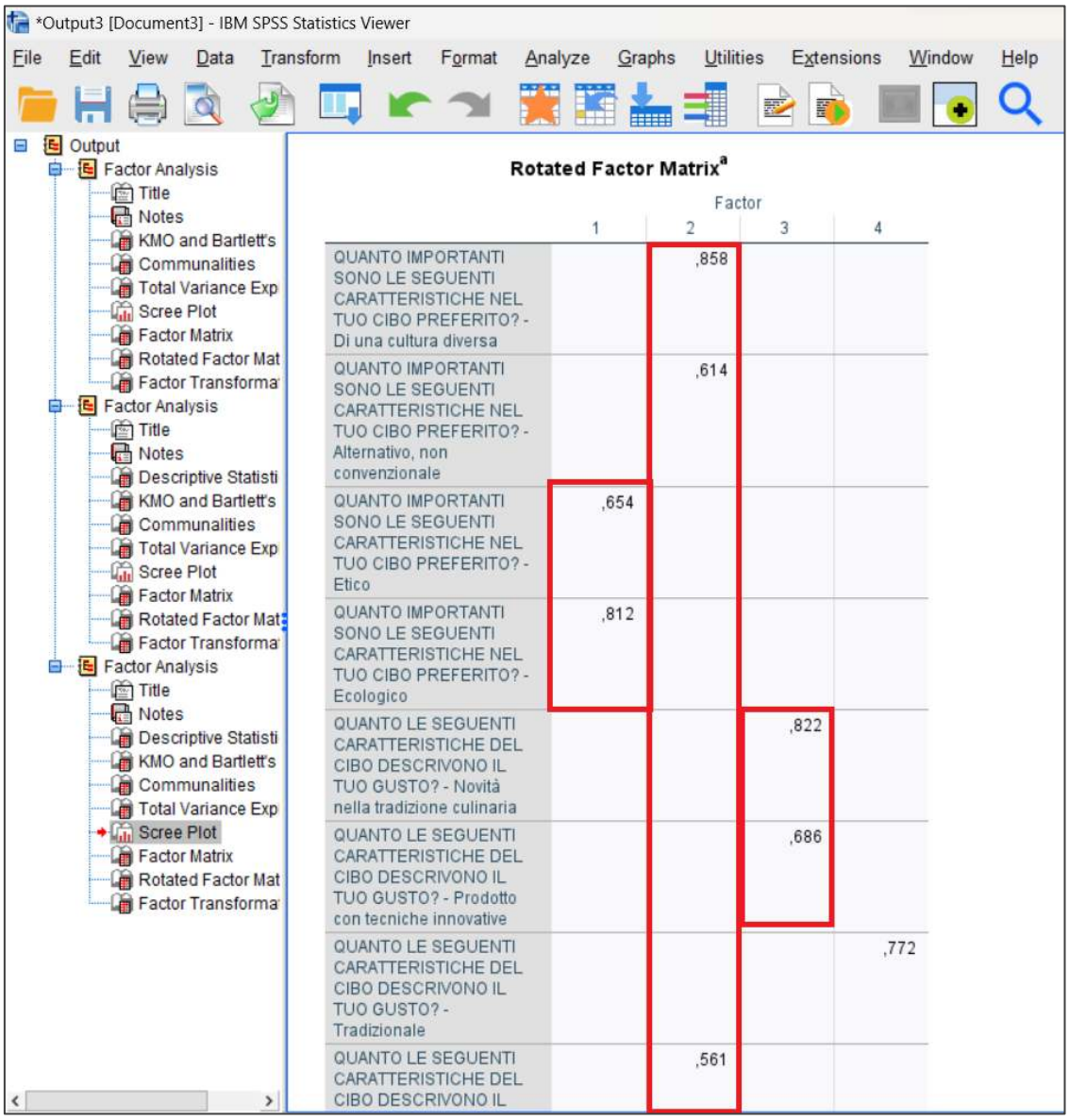
2.3.7. What is Varimax rotation?

Varimax rotation is a **specific type of orthogonal rotation** designed to simplify the interpretation of factors. The Varimax method **maximizes the variance** of squared loadings ***within*** each factor while **minimizing the variance** of squared loadings ***between*** factors (Kaiser, 1958). After Varimax rotation, each factor comprises **variables with high loadings on that factor** and **low loadings on other factors**.

2.3.8. Why is the Varimax Method so popular?

The popularity of Varimax rotation stems from its ability to **produce a solution where each factor is primarily associated with a subset of variables**, as in Fig. 9. This method enforces orthogonality, ensuring independence between factors. The result is distinct, non-overlapping factors. The production of relatively uncorrelated factors facilitates the identification of unique contributions from each variable to each factor and from each factor to the dataset.

Figure 9. *Orthogonality Among Factors Achieved through Varimax Rotation*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1 2 3 4
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa ,858
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale ,614
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico ,654
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Ecologico ,812
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Novità nella tradizione culinaria ,822
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto con tecniche innovative ,686
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Tradizionale ,772
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL ,561

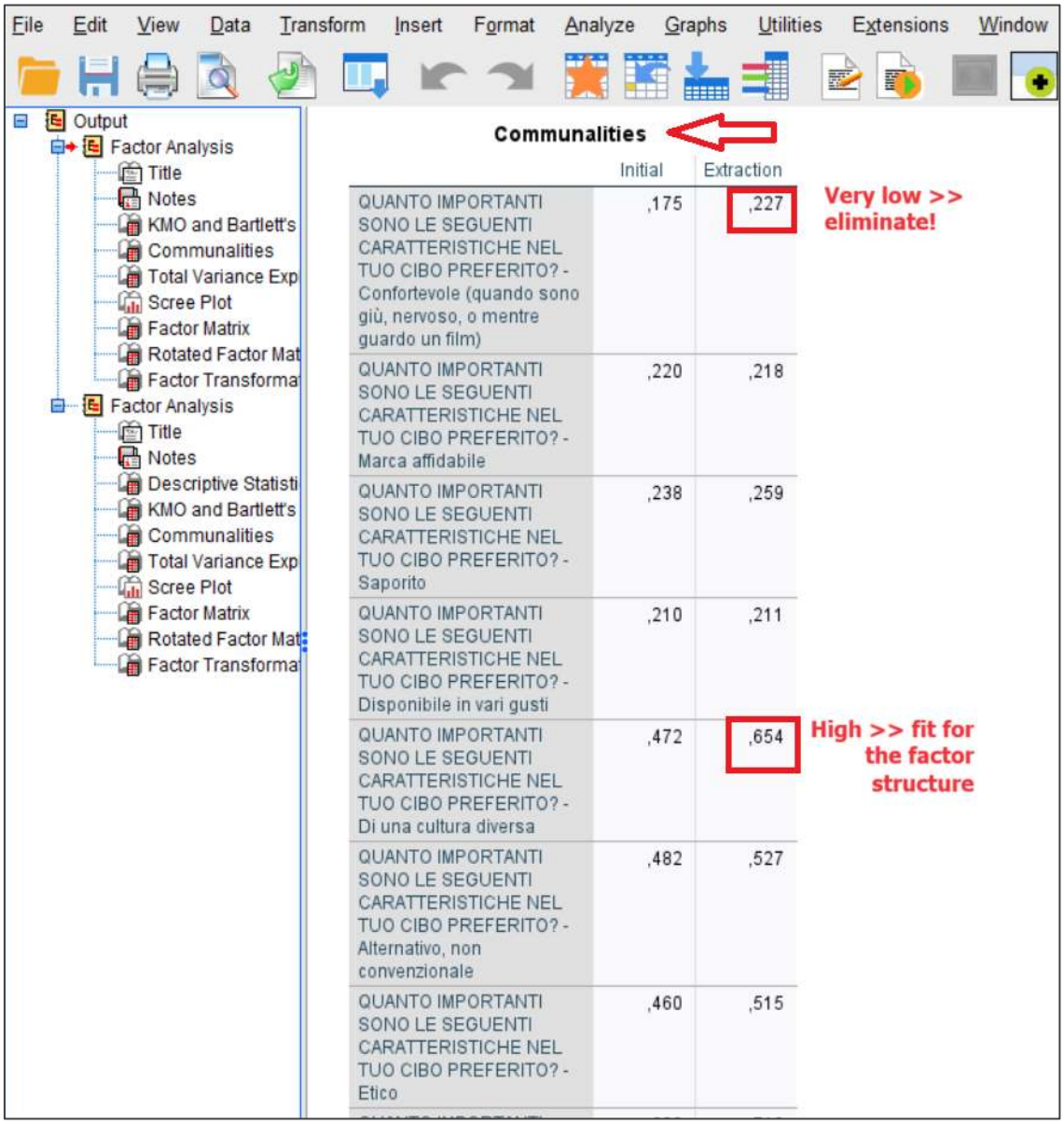
2.3.9. What is communality?

Communality values are crucial outputs in factor analysis. Ranging between 0 and 1, communality assesses the extent to which factors capture the variance in observed variables—how much the extracted factors have in common with each variable.

Communality represents the proportion of the variance in an observed variable explained by underlying latent factors. In simpler terms, it indicates how much of the variable's variance is accounted for by the factors. These values are pivotal in identifying variables that may be considered for elimination or retention within a factor model.

A communality value close to 1 suggests effective representation by the factors, while a value near 0 indicates poor explanation. Variables with low communality values may not be well-suited for factor analysis and could be candidates for removal from the analysis, as they contribute minimally to identifying the underlying structure (Fig. 10).

Figure 10. *Table of Communalities Displaying Values of Variables Considered for Elimination and Retention in the Factor Structure*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Factor Analysis
Title
Notes
KMO and Bartlett's
Communalities
Total Variance Exp
Scree Plot
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Very low >> eliminate!
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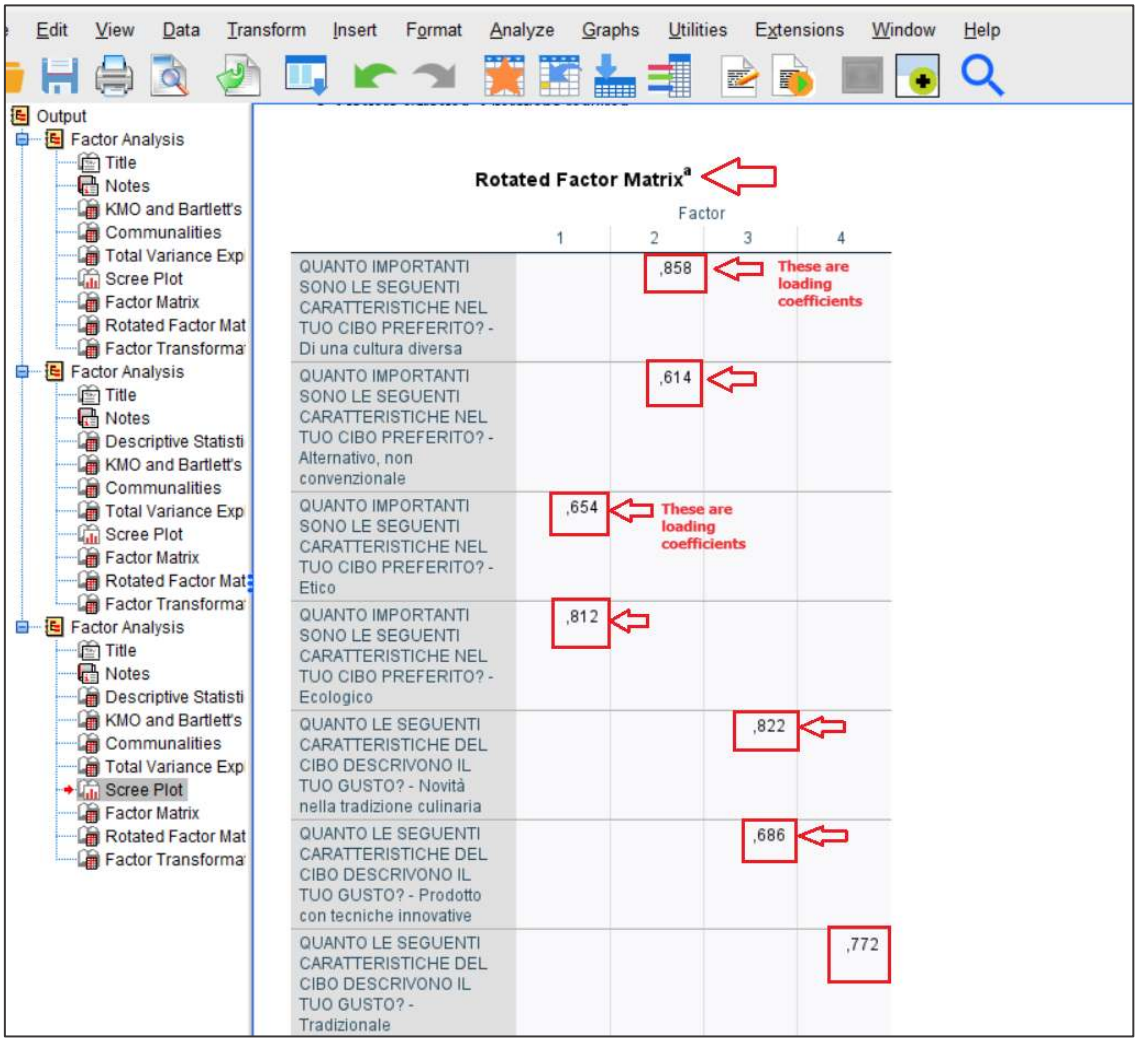
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Saporito ,238 ,259
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Disponibile in vari gusti ,210 ,211
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa ,472 ,654
High >> fit for the factor structure
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale ,482 ,527
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico ,460 ,515

2.3.10. What are Loading Coefficients?

Within the factor table matrix, loading coefficients depict the relationships between observed variables and underlying latent factors, revealing how much each observed variable contributes to or loads on each factor.

In a factor table matrix, each row corresponds to an observed variable, and each column represents a latent factor. Loading coefficients, displayed in each box, indicate the extent to which observed variables are associated with latent factors (Fig. 11). Variables with consistently low loadings across all factors may be considered for elimination from the analysis, as they contribute minimally to explaining the underlying structure. In an effective factorial structure, each variable should uniquely load at least 0.6 on a factor. Similarly, in a well-structured factorial model, each variable should share a commonality of at least 0.6 with the factor, representing at least 60% of the variance in the variable.

Figure 11. *Loading Coefficients showing variables' prevailing load on each Factor*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,858
These are loading coefficients
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale
,614
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico
,654
These are loading coefficients
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,812
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Novità nella tradizione culinaria
,822
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto con tecniche innovative
,686
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Tradizionale
,772

2.3.11. How are communality and loading coefficients used in Factor Analysis?

Communality is commonly employed in conjunction with factor loadings to evaluate the model's quality and the appropriateness of variables in representing

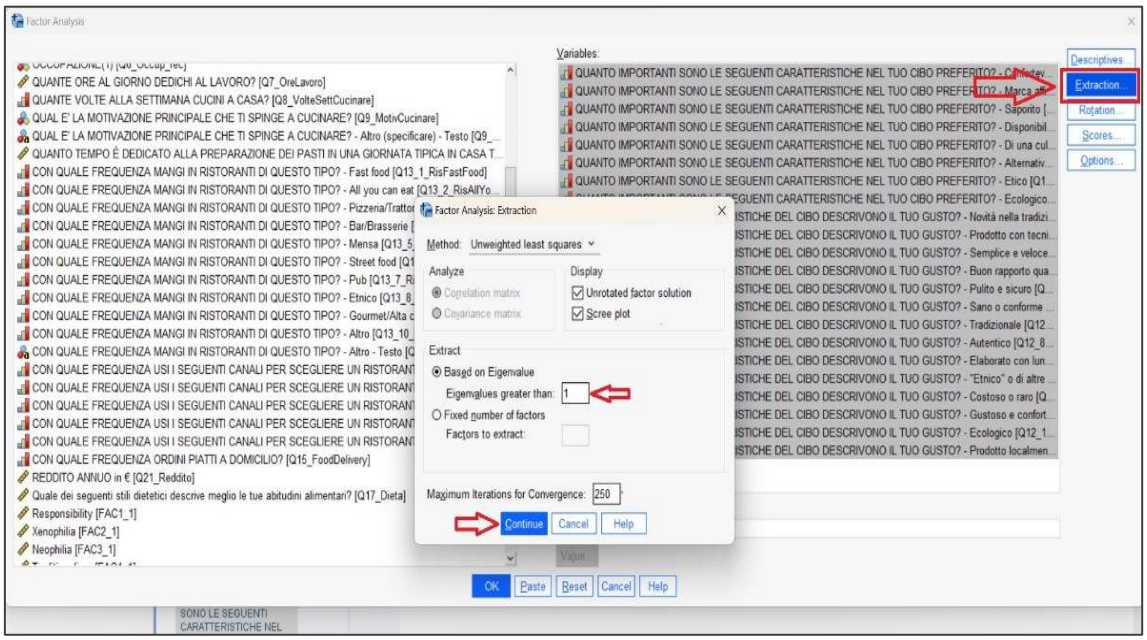
underlying latent constructs. When evaluated together, loading coefficients and communalities offer valuable insights into whether a variable should be retained or eliminated by a factor model.

Researchers frequently examine both loading coefficients and communality values to inform decisions about the utility of variables in the factor structure and analysis. Generally, variables with low communalities also exhibit low loading factors in the factor matrix table. In cases of conflicting values, such as a loading factor higher than 0.5 within at least one factor and a communality lower than 0.5, the decision to eliminate a variable is guided by communality.

2.3.12. What is an Eigenvalue ("Autovalore")?

Eigenvalues play a crucial role in determining the appropriate number of factors to retain in the correlation matrix. Factors with higher eigenvalues explain a greater proportion of the variance in the data and are generally deemed more important in representing the underlying structure of the observed variables. The minimum eigenvalue threshold for a factor is often set at 1, considered reasonable because it ensures that the retained factors in the model explain at least as much variance as a single observed variable. Factors with eigenvalues less than 1 are considered less important. This is the reason why SPSS presents a default Eigenvalue of 1 under the factor extraction criteria (Fig. 12).

Figure 12. *SPSS Default Setting of Eigenvalue Threshold greater than 1*



Why is an eigenvalue greater than **1** so significant? Because it indicates that the factor contributes as much as a single observed variable would on its own.

Factors with eigenvalues less than 1 are often seen as explaining less variance than individual variables and may not provide substantial additional insight. But above all, factors with eigenvalue lower than 1 do not fulfil the factor analysis goal: reducing dimensionality. Retaining factors with eigenvalues greater than 1 helps ensure that the retained factors are informative and capture a meaningful amount of the variance in the data while reducing the dimensionality.

2.3.13. What is a Screeplot?

A screeplot is a graphical representation used in factor analysis to help decide the optimal number of factors to retain. The screeplot visualization needs to be set manually in SPSS when determining the criteria for factor extraction (Fig. 13).

Figure 13. *SPSS Setting of a Screeplot*

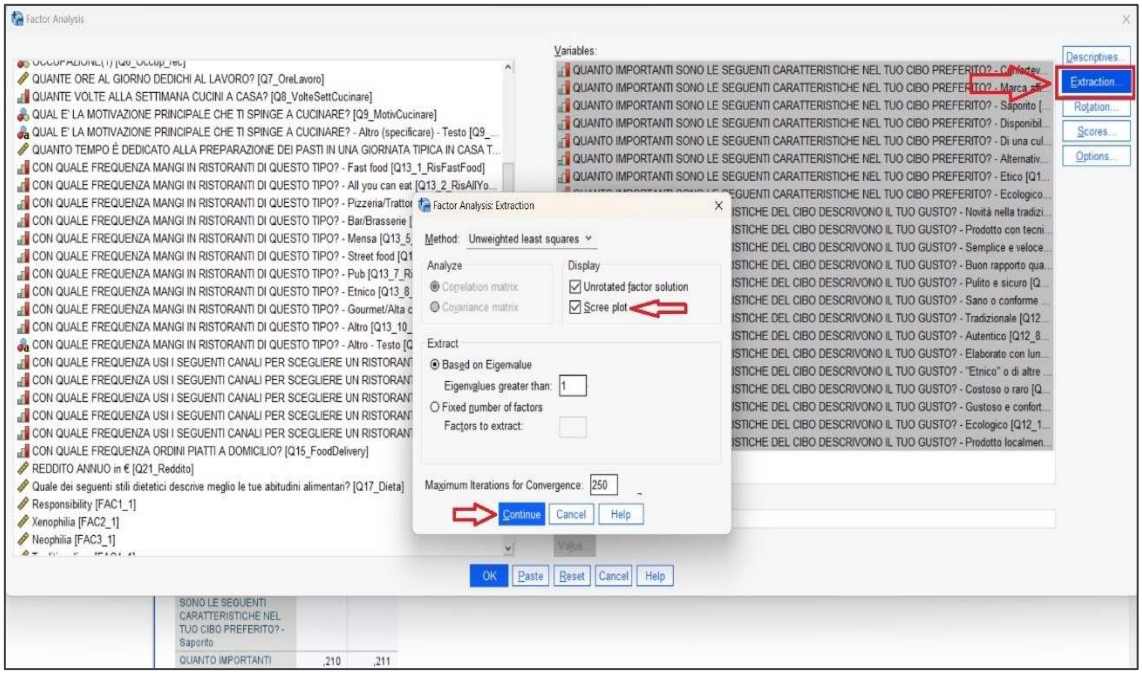
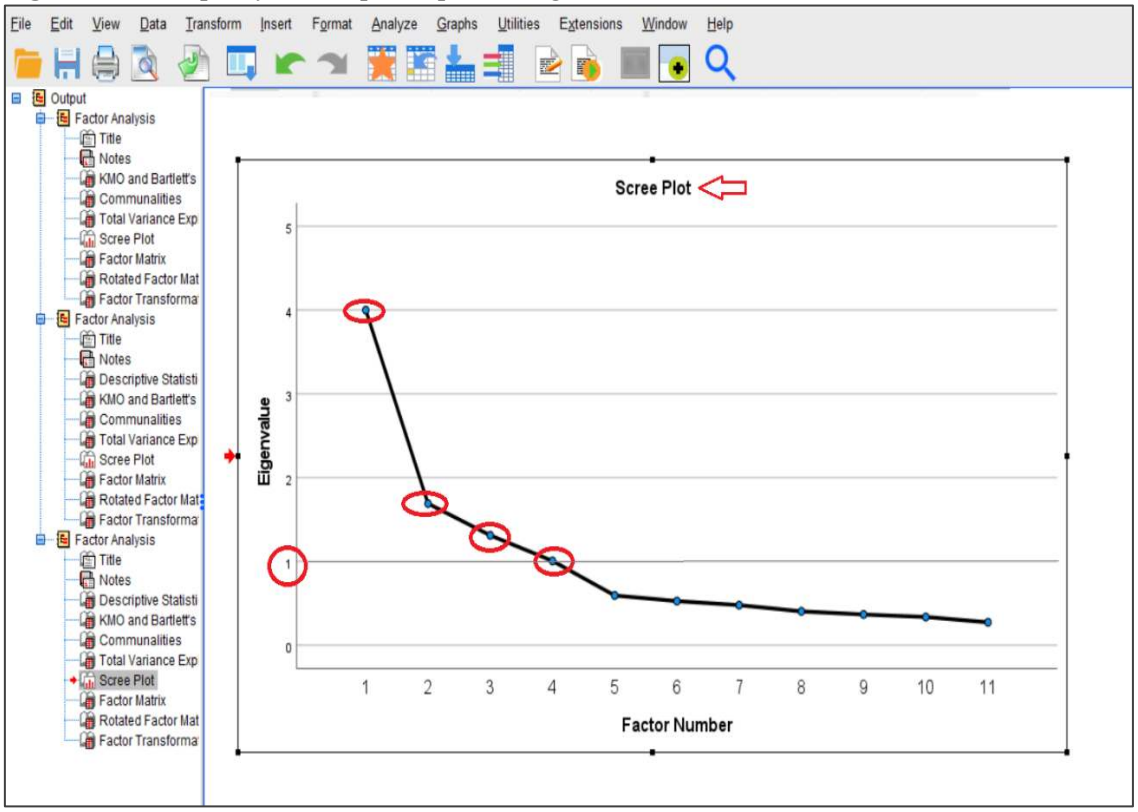


Figure 14. *Example of a Screeplot representing a 4-Factor model*



The screeplot typically takes the form of a jagged line graph, with each point representing factor eigenvalues plotted in descending order. The plot exhibits a sharp decline in eigenvalues, with more significant gaps at the beginning, where the first factors have higher eigenvalues and are distinctly separated from each other. As the graph progresses, the eigenvalues decrease in magnitude until the line levels off. This point where the plot levels off is commonly referred to as the 'elbow,' and it serves as an indicator of the number of factors to retain in the factor structure (Fig. 14).

Chapter 3

Factor Analysis to explore evolving consumer patterns

3.1. Factor Analysis to explore antinomies and values driving food-related patterns in a sample of Italian consumers

According to Alan Warde (1997), one of the most relevant scholars in the sociological field of food consumption studies, whose analysis distinguishes itself through an original combination of practice-theory and socio-cultural approaches to taste, there are four fundamental taste antinomies at the basis of food preferences. Antinomies represent fundamental dilemmas within omnivorous culture, involving claims and counterclaims that underlie consumer choices. In Warde's own words:

> They are permanent features of the modern predicament, according to which being competent means to be able to decide between alternative courses of action (Warde, 1997: 56).

Antinomies can be discerned in various forms of consumption, but they are particularly notable in food-related practices and preferences. These antinomies configure as four fundamental, long-standing oppositions that outline values and priorities guiding food appreciation and dietary decisions (Tab. 1).

Table 1. *The four antinomies identified by Warde as guiding food taste*

Novelty	⇔	Tradition
Health	⇔	Indulgence
Economy	⇔	Extravagance
Care	⇔	Convenience

Since 1997, food antinomies have evolved alongside shifting consumer claims and awareness. Consequently, we can assert that in contemporary times, in addition to the original four, at least four more dilemmas guide consumer priorities: global/local, fake/authentic, ethical/unethical, and eco-friendly/non-eco-friendly. A fifth concern, i.e., risky/safe, has gained prominence, especially following the health emergency of 2020.

Let's imagine wanting to explore the existence of these antinomies in consumption trends manifested in a sample of Italian consumers from February 2022 to April 2023, during the era of the so-called 'new normality' post-COVID-19.

We designed a survey consisting of 50 questions (refer to Table 2) focused on food-consumer preferences and practices related to consumption. The survey was administered to a convenient sample of 729 valid Italian respondents located in various parts of Italy.

Table 2. *The survey about food consumer preferences and related practices*

Q1	Genere *Gender*
Q2	Eta' *Age*
Q3	Stato civile *Civil Status*
Q4	Chi vive con lei in casa? *Who lives with you at home?*
Q5	Livello di istruzione raggiunto *Level of education achieved*
Q6	Occupazione *Occupation*

Q7	Quante ore al giorno dedichi al lavoro? *How many hours a day do you dedicate to work?*
Q8	Quante volte alla settimana cucini a casa? *How many times a week do you cook at home?*
Q9	Qual e' la motivazione principale che ti spinge a cucinare? – scegliere tra opzioni *What is the main motivation that drives you to cook? - selected choice*
Q10	Quanto tempo è dedicato alla preparazione dei pasti in una giornata in casa tua? *How much time is dedicated to meal preparation in a day at your home?*
Q11	Quanto è importante la seguente caratteristica nel tuo cibo preferito - confortevole (quando sono giù, nervoso, o mentre guardo un film) *How important is the following characteristic in your favorite food - comfortable (when I am down, nervous, or while watching a movie)*
Q12	Quanto è importante la seguente caratteristica nel tuo cibo preferito - marca affidabile *How important is the following characteristic in your favorite food - reliable brand*
Q13	Quanto è importante la seguente caratteristica nel tuo cibo preferito - saporito o familiare *How important is the following characteristic in your favorite food - tasty or familiar taste*
Q14	Quanto è importante la seguente caratteristica nel tuo cibo preferito - disponibile in vari gusti *How important is the following characteristic in your favorite food - available in various flavors*
Q15	Quanto è importante la seguente caratteristica nel tuo cibo preferito - di una cultura diversa *How important is the following characteristic in your favorite food - from a different culture*
Q16	Quanto è importante la seguente caratteristica nel tuo cibo preferito - alternativo, non convenzionale *How important is the following characteristic in your favorite food - alternative, unconventional*
Q17	Quanto è importante la seguente caratteristica nel tuo cibo preferito - etico (benessere animale, equo e solidale) *How important is the following characteristic in your favorite food - ethical (animal welfare, fair trade)*
Q18	Quanto è importante la seguente caratteristica nel tuo cibo preferito - ecologico (biologico, a km0, di stagione) *How important is the following characteristic in your favorite food - ecological (organic, local, seasonal)*
Q19	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - novità nella tradizione culinaria *How much the following characteristics of food describe your taste? - novelty in culinary tradition*
Q20	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - prodotto con tecniche innovative *How much the following characteristics of food describe your taste? - produced with innovative techniques*
Q21	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - semplice e veloce da preparare *How much the following characteristics of food describe your taste? - simple and quick to prepare*
Q22	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - buon rapporto qualità-prezzo *How much the following characteristics of food describe your taste? - good value for money*
Q23	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - pulito e sicuro *How much the following characteristics of food describe your taste? - clean and safe*
Q24	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - sano o conforme a una dieta *How much the following characteristics of food describe your taste? - healthy or compliant with a diet*
Q25	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? – tradizionale *How much the following characteristics of food describe your taste? - traditional*
Q26	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? – autentico *How much the following characteristics of food describe your taste? - authentic*
Q27	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - elaborato con lunga preparazione *How much the following characteristics of food describe your taste? - elaborately prepared*
Q28	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - "etnico" o di altre culture *How much the following characteristics of food describe your taste? - "ethnic" or from other cultures*
Q29	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - costoso o raro *How much the following characteristics of food describe your taste? - expensive or rare*

Q30	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - gustoso e confortevole *How much the following characteristics of food describe your taste? - tasty and comfortable*
Q31	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? – ecologico *How much the following characteristics of food describe your taste? - ecological*
Q32	Quanto le seguenti caratteristiche del cibo descrivono il tuo gusto? - prodotto localmente *How much the following characteristics of food describe your taste? - locally produced*
Q33	Con quale frequenza mangi in ristoranti di questo tipo? - fast food *How often do you eat at restaurants of this type? - fast food*
Q34	Con quale frequenza mangi in ristoranti di questo tipo? - all you can eat *How often do you eat at restaurants of this type? - all you can eat*
Q35	Con quale frequenza mangi in ristoranti di questo tipo? - pizzeria/trattoria *How often do you eat at restaurants of this type? - pizzeria/trattoria*
Q36	Con quale frequenza mangi in ristoranti di questo tipo? - bar/brasserie *How often do you eat at restaurants of this type? - bar/brasserie*
Q37	Con quale frequenza mangi in ristoranti di questo tipo? – mensa *How often do you eat at restaurants of this type? - cafeteria*
Q38	Con quale frequenza mangi in ristoranti di questo tipo? - street food *How often do you eat at restaurants of this type? - street food*
Q39	Con quale frequenza mangi in ristoranti di questo tipo? – pub *How often do you eat at restaurants of this type? - pub*
Q40	Con quale frequenza mangi in ristoranti di questo tipo? – etnico *How often do you eat at restaurants of this type? - ethnic*
Q41	Con quale frequenza mangi in ristoranti di questo tipo? - gourmet/alta cucina *How often do you eat at restaurants of this type? - gourmet/fine dining*
Q42	Con quale frequenza mangi in ristoranti di questo tipo? – altro (specifica) *How often do you eat at restaurants of this type? – other (specify)*
Q43	Con quale frequenza usi i seguenti canali per scegliere un ristorante? - guide gastronomiche *How often do you use the following channels to choose a restaurant? - gastronomic guides*
Q44	Con quale frequenza usi i seguenti canali per scegliere un ristorante? - programmi tv di cucina *How often do you use the following channels to choose a restaurant? - cooking TV programs*
Q45	Con quale frequenza usi i seguenti canali per scegliere un ristorante? - social media (Tripadvisor, Instagram, TikTok, Facebook, ecc.) *How often do you use the following channels to choose a restaurant? - social media (Tripadvisor, Instagram, TikTok, Facebook, etc.)*
Q46	Con quale frequenza usi i seguenti canali per scegliere un ristorante? - critiche gastronomiche professionali *How often do you use the following channels to choose a restaurant? - professional gastronomic reviews*
Q47	Con quale frequenza usi i seguenti canali per scegliere un ristorante? – passaparola *How often do you use the following channels to choose a restaurant? - word of mouth*
Q48	Con quale frequenza ordini piatti a domicilio? *How often do you order dishes for home delivery?*
Q49	Reddito annuo in € *Annual income in €*
Q50	Quale dei seguenti stili dietetici descrive meglio le tue abitudini alimentari? *Which of the following dietary styles best describes your eating habits?*

The survey generated a database with 71 variables, each representing self-reported behaviors or beliefs in the observed cases. To examine the presence of underlying food antinomies influencing these behaviors and beliefs, Factor Analysis emerges as the most appropriate data analysis technique.

As clarified in the previous chapters, from a statistical standpoint, Factor Analysis is a technique for data reduction. It reduces the complexity of a dataset to a smaller number of common factors that explain the variance of the most important output variables, which are found to be correlated with these factors.

Factor Analysis provides a (factorial) structure (or solution) that:

1. Organizes original variables as linear combinations of a reduced number of hidden latent variables, called 'factors.' These new variables ('factors') share communalities with the original variables and aggregate them into new variables.
2. Maximizes communality (the extracted factors aim to explain as much as possible of the overall variation of the original variables).
3. Minimizes unexplained variation (or residual) between factors.

These factors are determined through maximum likelihood estimation (MLE) with the original variables, and this regression captures (explains) most of the variance in the original data matrix. In summary, Factor Analysis enables the identification of the most significant variables among the many behaviors and beliefs observed in your dataset.

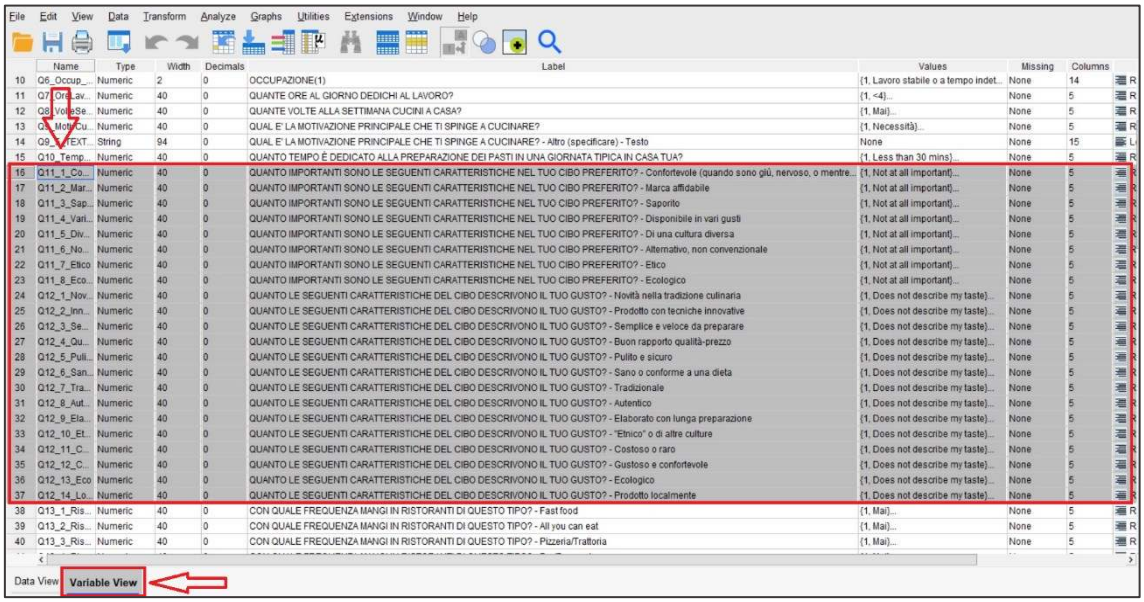
To demonstrate how to implement Factor Analysis of this kind in a database, the following sections will utilize the data collected through the aforementioned survey. The survey is presented in its original language, Italian, with an English translation in italics. Additionally, the version of the SPSS software used is also in Italian.

In this specific case, to identify the existence of hidden patterns referred to as taste antinomies, we will exclusively use 'evaluative' variables in our Factor Analysis. These variables, namely Q11 through Q32, express values (importance attached to specific characteristics of food) and preferences (characteristics of one's own taste).

3.2. Preparation of the Factor Analysis on SPSS[3]

Open your dataset in variable view ('vista variabile'). Identify the variables you wish to include in your Factor Analysis (Fig. 1).

Figure 1. *Selection of Variables for Factor Analysis*


File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help
Name Type Width Decimals Label Values Missing Columns
Data View
Variable View

[3] In parentheses, you'll find the Italian translation of the functions available in the Italian version of the software.

Given that our objective is to use this technique for identifying hidden patterns influencing self-reported beliefs, preferences, and behaviors, only the variable 'evaluative' will be included in our analysis.

In marketing analysis, particularly for Factor Analysis (FA), variables related to preferences, opinions, importance, attitudes, etc., are commonly used. Evaluative variables can be influenced by underlying ('synthesizing') hidden patterns of tastes and values that explain part of the original variables' variability.

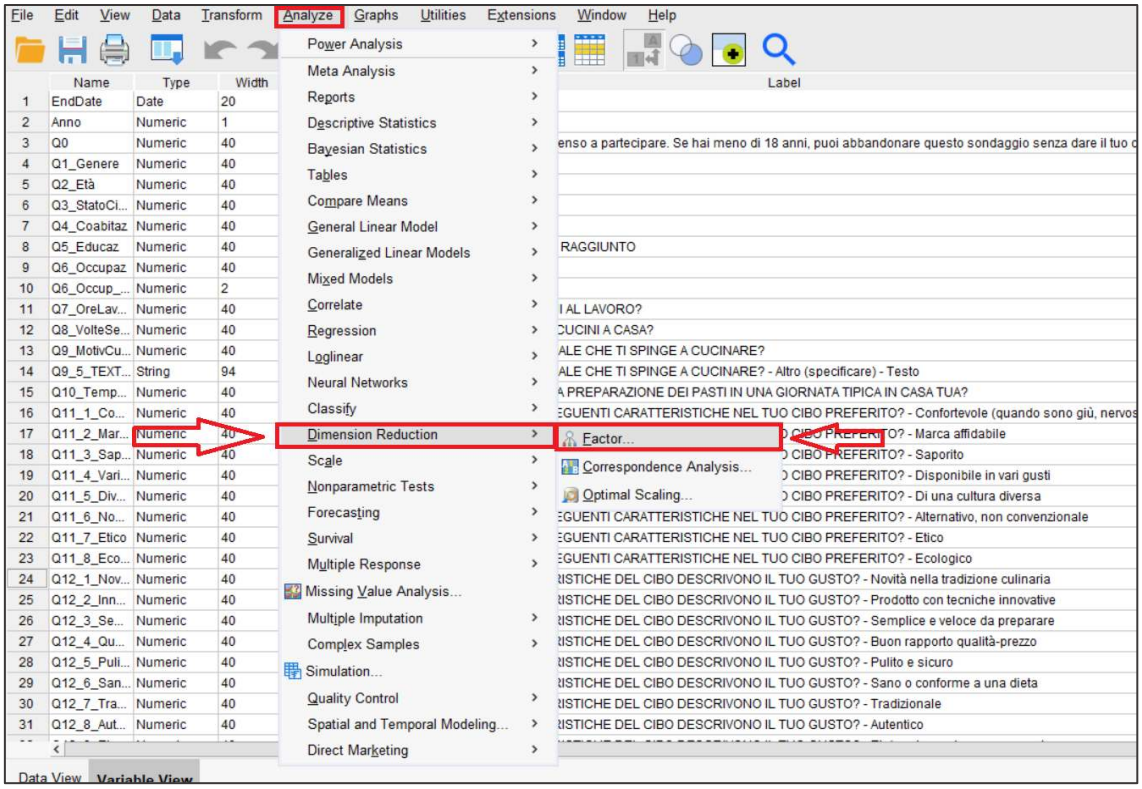
It is advisable to use the same type of variables in Factor Analysis, for example, all ordinal scales with the same interval, such as all 5-point scales in this case. If the chosen variables have the same interval (e.g., all on a 5-point scale), standardization is unnecessary. However, if your variables have different intervals (e.g., some on a 5-point scale and others as YES/NO), standardization is required. Hence, ensure your survey uses consistent point scales for variables and avoid dichotomic (e.g. yes/no variables) because "no" might be confused with "missing". Multiple choice questions are not suitable for Factor Analysis.

3.3. Step-by-step Factor Analysis: Let's begin!

It is important to recall that the PCA, ULS, and FA mechanisms aim to reduce the number of variables for analysis. In the SPSS analysis menu, therefore, this function is referred to as 'dimension reduction'.

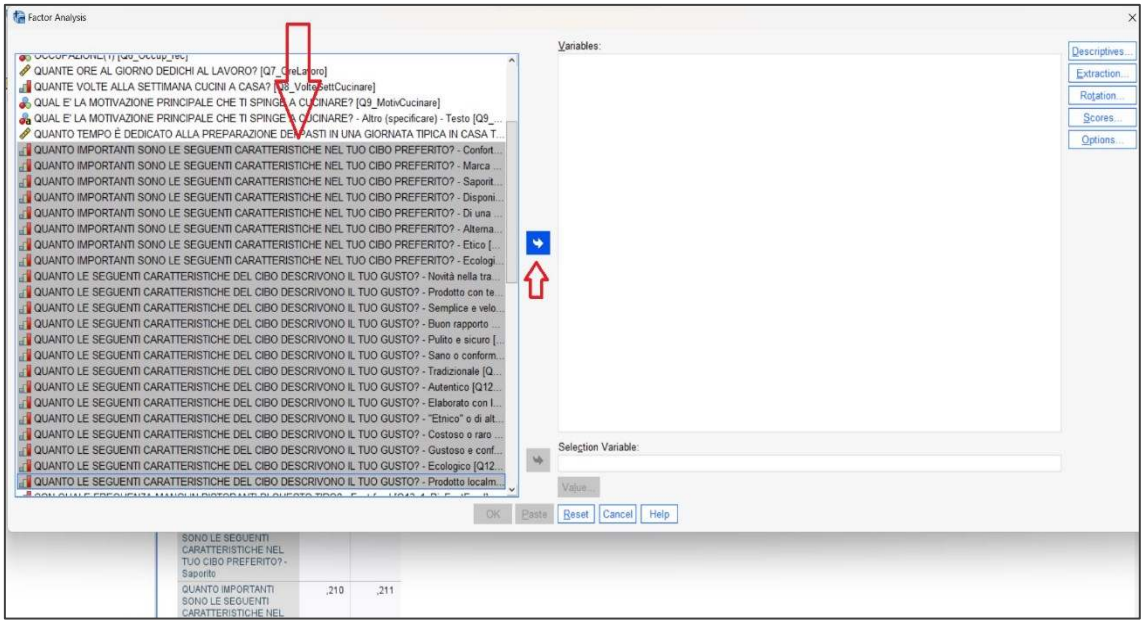
So, click on: 'Analyze' (analizza), a menu opens. Click on Dimension Reduction (riduzione dimensioni) and then on 'Factor' (fattore) (Fig. 2).

Figure 2. *Settings for implementing Factor Analysis*



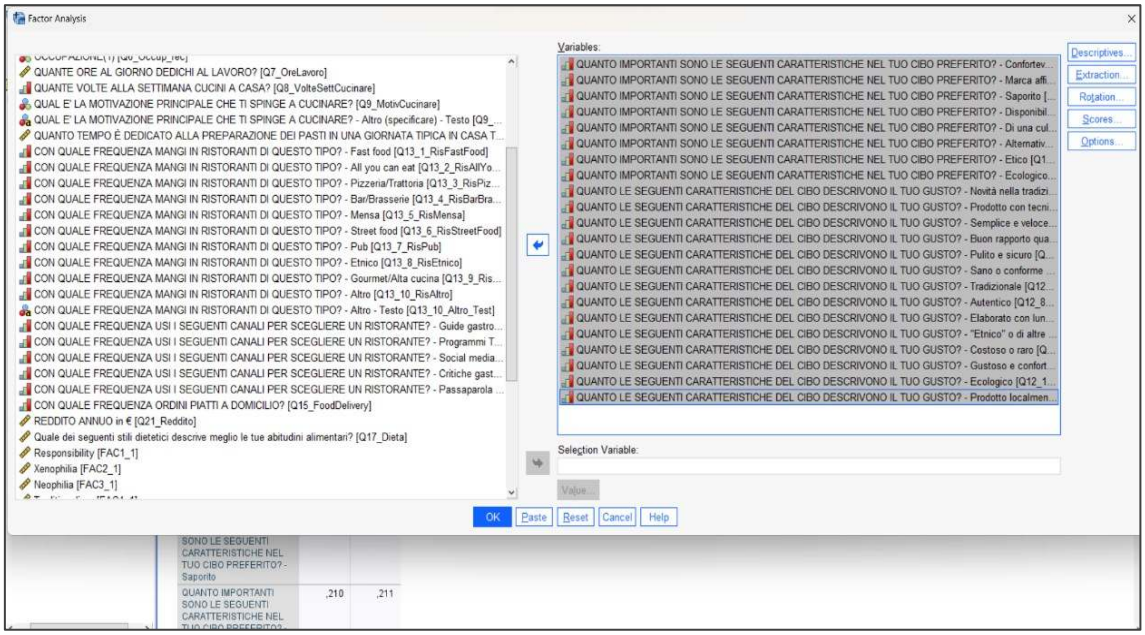
After clicking on the 'Factor' tag a menu will open. In the window on the left, all variables in the database will appear. Select the variables you wish to include in your analysis.

Figure 3. *Settings within the menu of Factor Analysis*



To move the selected variables into the 'Variables' (variabili) box, click on the small arrow between the two windows, as shown in Fig. 3. Ignore 'Selection variable' (variabile di selezione). Then click on 'OK'.

Figure 4. *Selected Variables for Factor Analysis Computation*



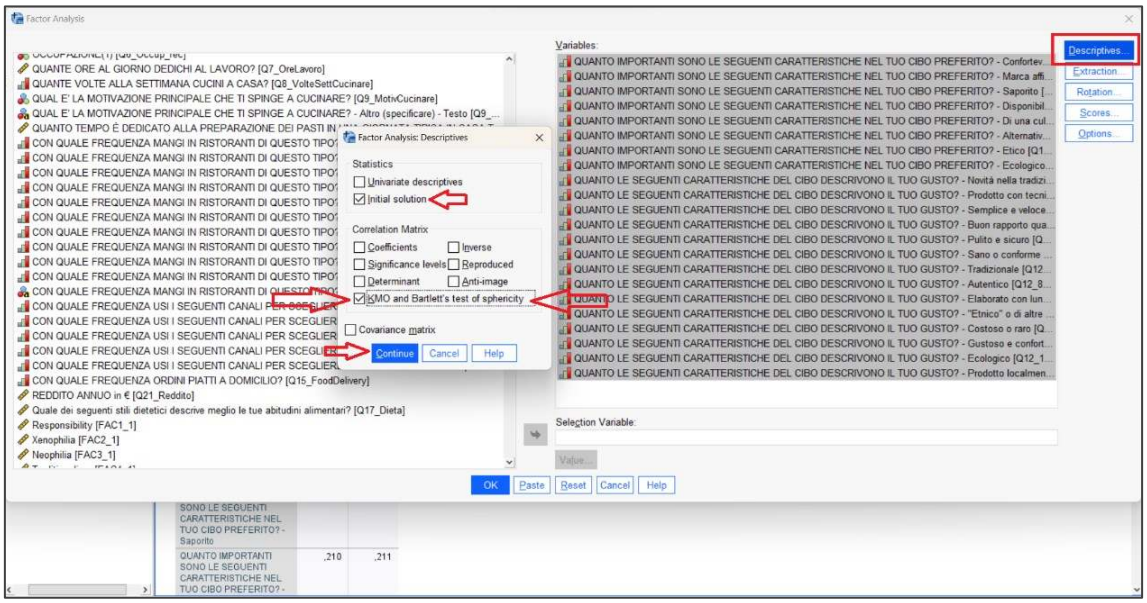
Next, let's set the parameters needed for the analysis.

In the first step, select the descriptive parameters necessary to determine if our variables are suitable for Factor Analysis. Click on 'Descriptives' (descrittive).

A menu opens, you'll find by default flagged 'Initial solution' (soluzione iniziale), keep it as it is. This means you choose to visualize the initial solution of the factor extraction. You can manually select 'Univariate descriptives' (descrittive univariate) if you wish to see the mean, standard deviation, and frequencies for each variable. I recommend not doing that here but separately as a preliminary check before starting with Factor Analysis.

Then, manually click on 'KMO test and Bartlett's sphericity' to assess if statistical parameters are met for Factor Analysis. Remember, these are crucial parameters to determine the applicability of Factor Analysis to your sample. Finally, click on 'Continue' (Fig. 5).

Figure 5. *Descriptive parameters for Factor Analysis Computation*



To modify the methods and criteria for factor extraction, return to the main menu.

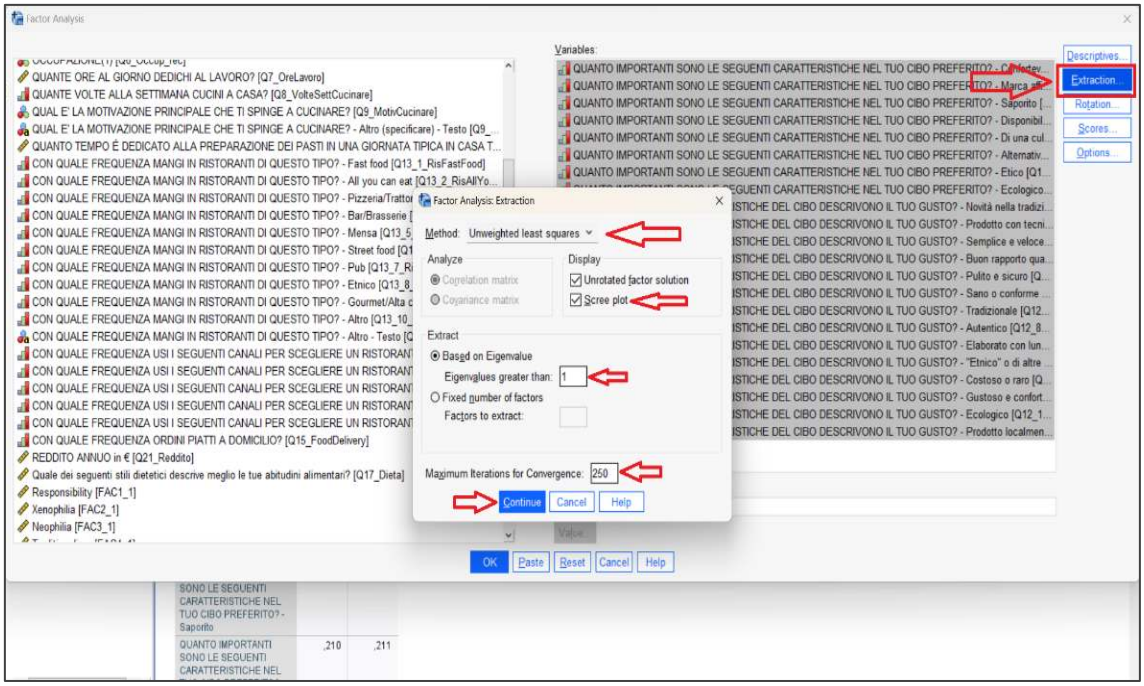
Click on the second button, labeled 'Extraction' ('estrazione').

In the menu that opens, you will find the default selection of the extraction method as 'principal component-PCA' (componenti principali). PCA aims to reduce the dimensionality of the data by identifying new variables (principal components) that are linear combinations of the original variables. Each component is designed to explain the maximum variation in the data. While PCA and Factor Analysis yield similar outputs, it's crucial to note that they are technically distinct. PCA is effective with continuous and symmetric data.

In our context, Factor Analysis seeks to unveil the underlying structure of the data by computing latent factors explaining relationships between observed variables. ***For this purpose, the Unweighted Least Squares method (ULS, in Italian 'minimi quadrati non pesati') is more suitable than the Principal Component method***. ULS focuses on the structure of latent factors, especially when assuming that the factors are originally correlated. The ULS method is preferable when exploring latent factors without making a strong assumption of factor orthogonality, which is often the case in the study of human preferences, beliefs, and behaviors.

To proceed, click on the menu where 'Principal Component' is the default selection, then manually choose ‘Unweighted Least Squares method: ULS’ (minimi quadrati non pesati) (Fig. 6).

Figure 6. *Settings of methods and parameters for factor extraction*



ULS is the correct method of extraction for this kind of Factor Analysis.

Below ULS, you will find 'unrotated factor solution’ (soluzione fattoriale non ruotata) flagged by default. Keep it as is, indicating your preference to observe the initial factor structure extracted by the program before implementing any rotation, aiming for a higher level of orthogonality among factors (Fig. 6).

Next, manually select 'screeplot' (grafico scree) to visualize the number of extracted factors explaining the variance of the original variables and illustrating their interrelationships.

Ensure that 'Eigenvalue' (autovalore) is already set to 1, and leave it unchanged. This setting signifies that each factor will account for the variance of at least one variable. At this stage, ignore any other graph.

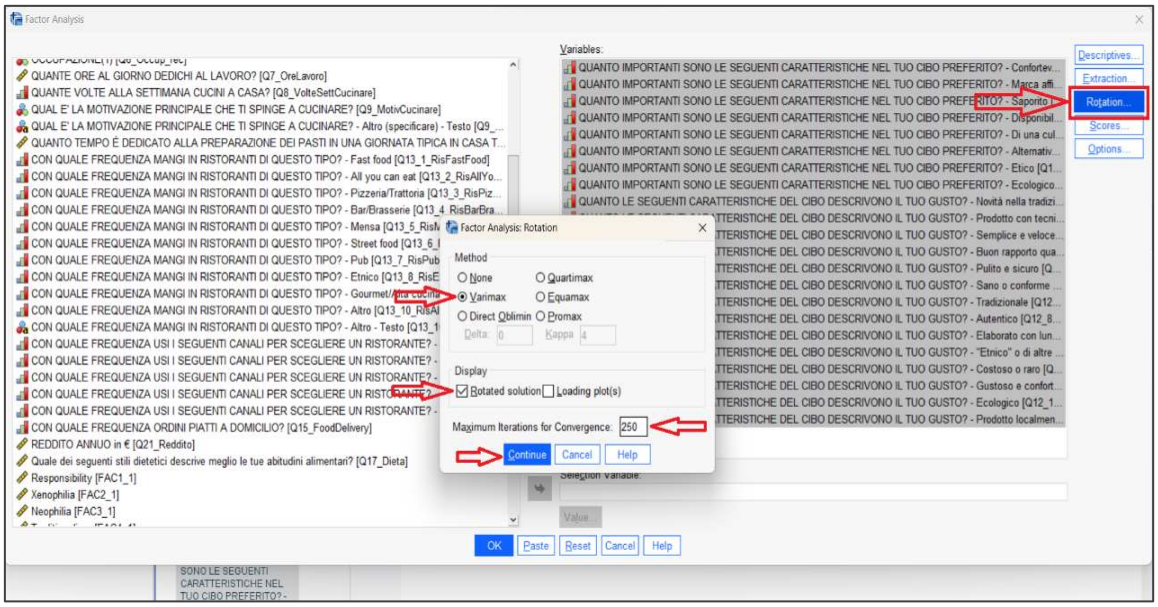
Manually add a 'zero' to the default maximum number of iterations to increase them. As detailed in Chapter 2, this precaution ensures an ample number of trials before the program achieves perfect convergence of the factorial model. Your Factor Analysis may require more than 25 iterations to attain the optimal solution (Fig. 6).

Click on 'Continue' to proceed.

The next step involves configuring the "rotation" setting. As explained in the previous chapter, rotation is a technique used to enhance orthogonality between factors in the model, thereby improving the structure of the factorial model and optimizing the relationships between the variables and the factors. This is crucial for effectively separating factors and making them more distinguishable and easily identifiable.

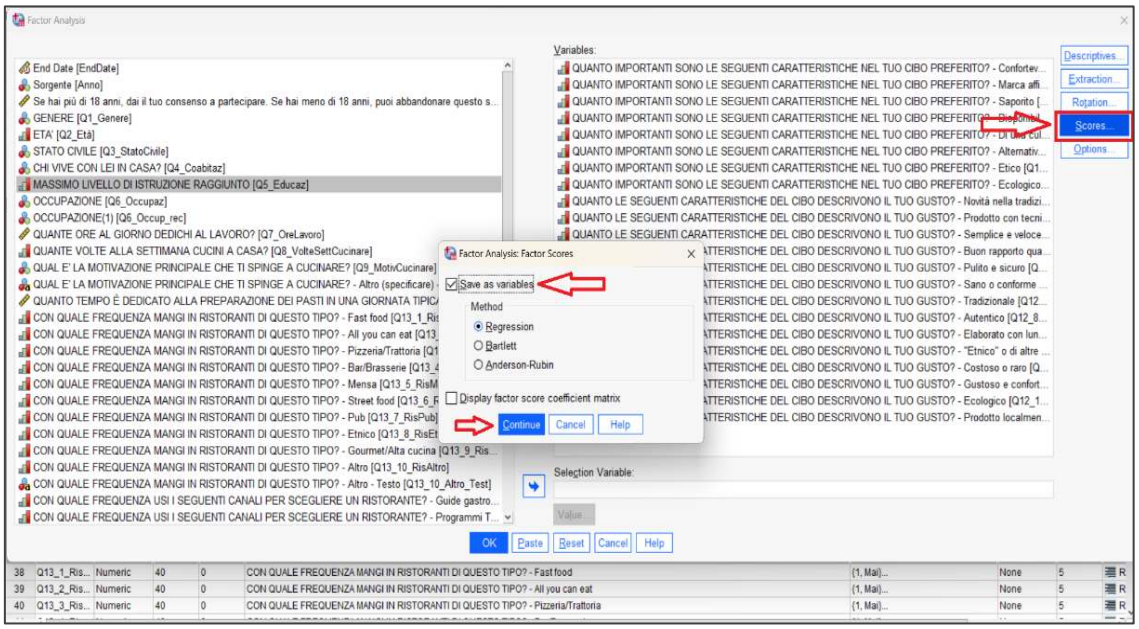
Click on ‘rotation’ (rotazione) and manually select "Varimax." (Fig. 7) This type of rotation is considered the best because it maximizes the variance of squared loadings within each factor while minimizing the variance of squared loadings between factors. This approach enhances the orthogonality of relationships, promoting the independence of the factors. Afterward, below, flag ‘Rotated solution’ (soluzione ruotata) to visualize the rotated structure. Click on ‘continue’ to proceed.

Figure 7. *Rotation of the extracted factor structure*



If you click on ‘scores’ (punteggi), you will be asked if you want to save the extracted variables in the database variable view (Fig. 8). At this stage, it is advisable not to save factors, i.e., not to select this setting. Factors should be saved at the very end of the Factor Analysis, when the researcher believes they have reached the best factor solution with the optimal number of variables.

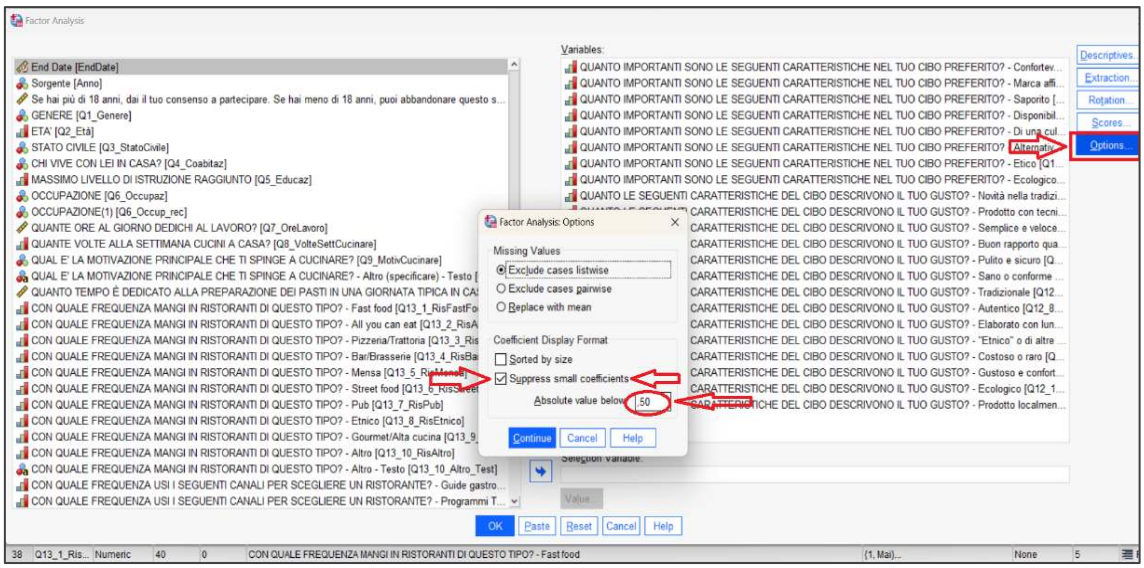
Figure 8. *Setting to save factors as variables*



The last setting concerns the visibility of values within the output factor tables. To configure this, select the last button labeled 'Options' (opzioni).

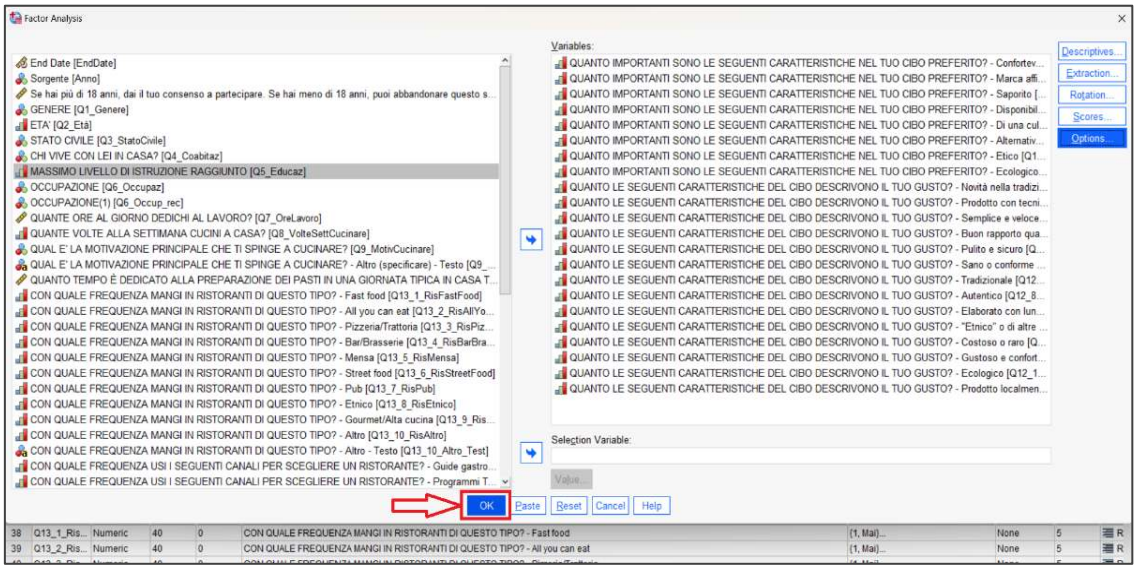
In the menu that opens, you will find 'Exclude cases listwise' (escludi casi listwise) flagged by default. Keep it as is; this means that missing values will be excluded from the analysis. Manually flag 'Suppress small coefficients' (elimina coefficienti piccoli). This implies that in the final rotated factor matrix, you will see only the correlation values of the variables higher than "0.50" (Fig. 9). This choice aims to make your final output table structure more readable and will facilitate the identification of variables weakly correlated with each factor. Rows with 'blank' boxes in the output factor matrix will indicate loading factors with coefficients lower than 0.5, prompting the exclusion of variables poorly correlated with the factors. Then click on 'continue' (continua).

Figure 9. *Eliminate small loading coefficients*



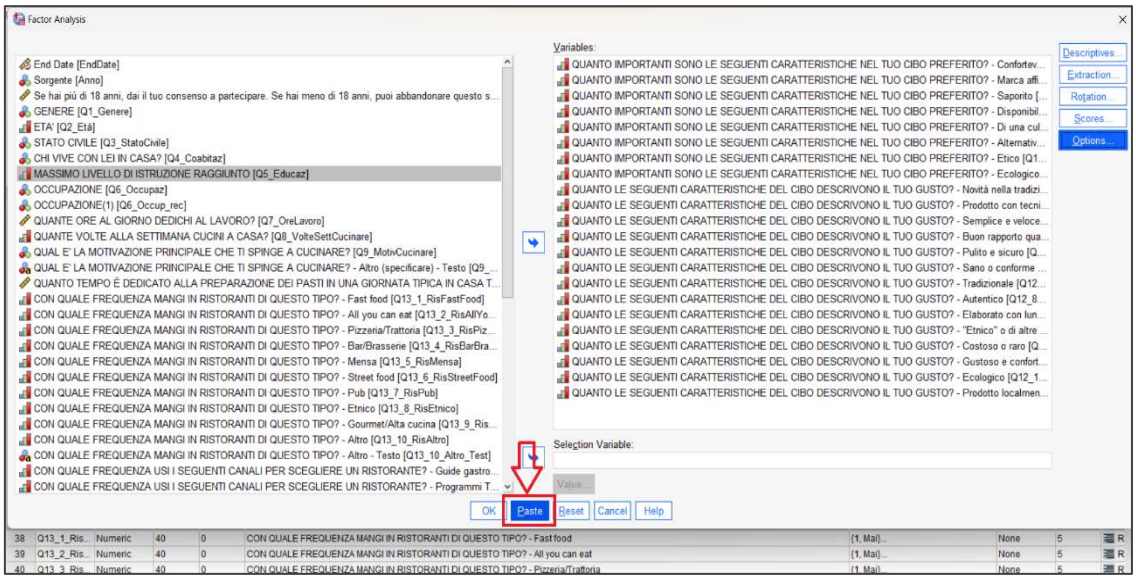
Once all these settings have been configured, click on 'OK' to initiate your Factor Analysis (Fig. 10).

Figure 10. *Launch your Factor Analysis with these settings*



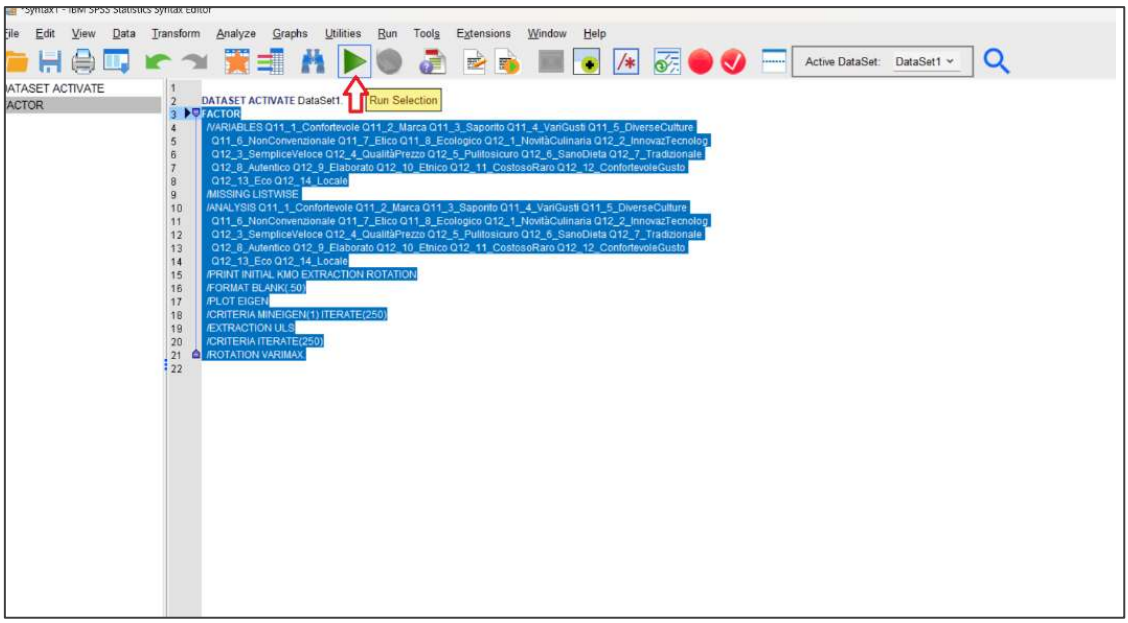
Alternatively, you may choose to click on ‘paste’ (incolla) (rather than on "OK") to save your settings as syntax (Fig. 11). This approach is highly recommended, especially in the case of Factor Analysis and other iterative techniques. It allows the researcher to directly modify settings or eliminate variables from the syntax strings, saving all the steps without manually adjusting settings in the dialogue windows.

Figure 11. *Save your Factor Analysis settings as syntax*



If you choose this second option, a syntax sheet opens where you'll find your settings saved as text strings. To execute this syntax and generate the output, select all the syntax (from 'FACTOR' to 'Varimax', making sure to include the final dot in your selection) and click on the green button (Fig. 12).

Figure 12. *Launch the syntax to generate your output*



Both solutions, either directly clicking on "OK" or creating a syntax and launching it, are viable options to generate your output.

3.4. Initial Output from the Conducted Factor Analysis

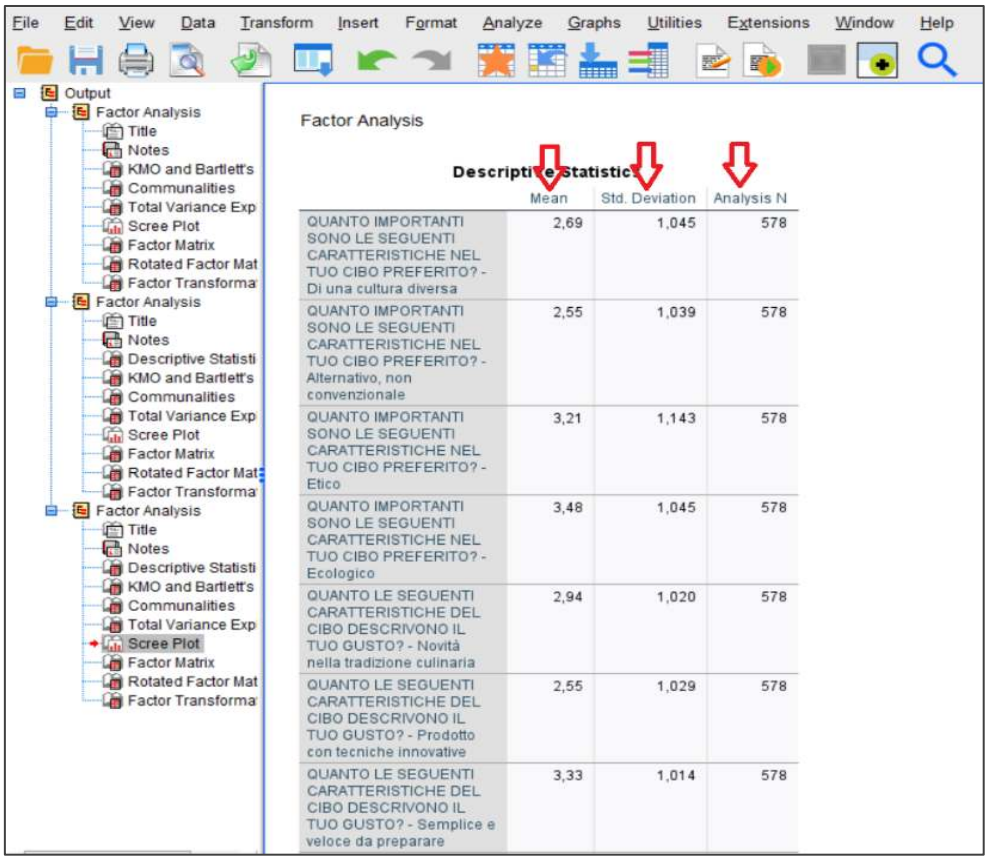
3.4.1. Descriptive statistics

The initial information in your output pertains to descriptive statistics, encompassing the mean, standard deviation, and frequencies (number of analyzed cases) for each variable (Fig. 13).

Descriptive preliminary statistics serve as a foundation for the subsequent steps in Factor Analysis, aiding in data preparation, ensuring it aligns with analysis assumptions, and assisting researchers in making informed decisions regarding variable inclusion, handling outliers, and interpreting factor loadings. The mean provides insights into the central tendency of the data, aiding in the interpretation of the overall distribution of each variable. Standard deviation measures the variation or dispersion in a set of values, and higher standard deviations indicate greater variability. Understanding the variability in the original variables is crucial for interpreting the strength and direction of relationships, such as those represented by factor loadings between variables and factors. Variables with low variability may have minimal impact on factor structures and could be considered for exclusion from the analysis.

Factor Analysis often assumes normal distribution of variables, and deviations from normality can influence results. Frequencies provide information about the number of cases analyzed for each variable. This is crucial when considering how missing values are handled in Factor Analysis and determining the actual number of cases included in the analysis.

Figure 13. *Descriptive Statistics in Factor Analysis Output*



3.4.2. Tests of Sample Adequacy for Factor Analysis

The second information appearing in the output is KMO Test and Bartlett's sphericity, i.e. two parameters used in factor analysis to assess the adequacy of the sample for conducting the analysis (Fig. 14).

Specifically, the KMO test evaluates the suitability of data for factor analysis by examining the proportion of variance among variables that might be common variance in the correlation patterns.

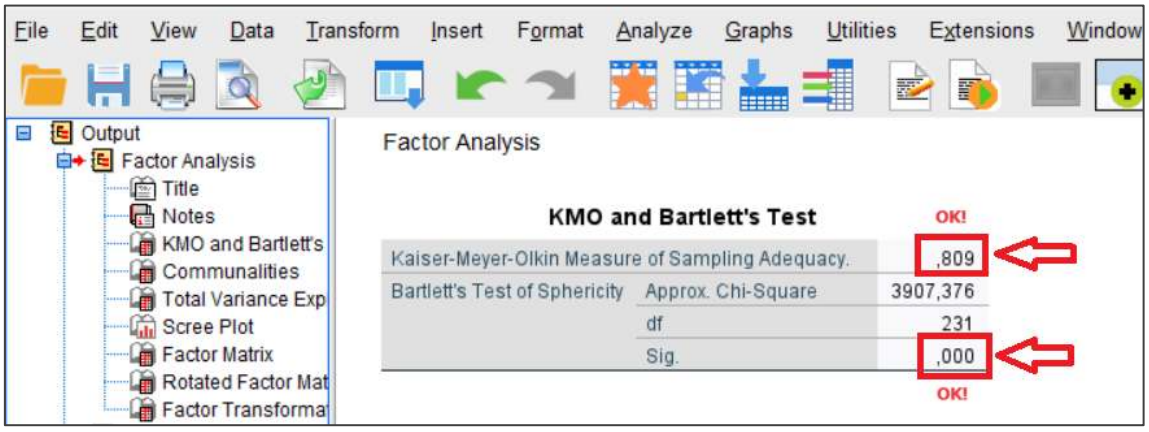
KMO test helps researchers determine whether the variables in their dataset share enough common variance to justify performing factor analysis. The KMO test, like many parameters assessing correlation strength, produces a statistic that falls within the range of 0 to 1. Higher values of KMO (closer to 1) indicate that the data is more suitable for factor analysis. Lower values of KMO (below 0.5, for example) suggest that the variables considered for the analysis share low variance and may not be suitable for factor analysis (Field, 2009: 647).

Following the estimates provided by Hutcheson & Sofroniou (1999), here's a general interpretation of KMO values:

- KMO < 0.5: The sampling is considered inadequate for factor analysis.
- 0.5 < KMO < 0.6: The sampling is marginal, and factor analysis may not be very reliable.
- 0.6 < KMO < 0.7: The sampling is mediocre, and the factor analysis may be suitable with caution.
- 0.7 < KMO < 0.8: The sampling is good, and factor analysis is likely to be useful.
- 0.8 < KMO < 0.9: The sampling is great, and factor analysis should work well.
- KMO > 0.9: The sampling is superb, and factor analysis is highly appropriate.

In the output depicted in Fig. 14, the KMO values are highly favorable (greater than 0.8), indicating a robust foundation for conducting factor analysis.

Figure 14. *Tests of Sample Adequacy for Factor Analysis*



Bartlett's sphericity test assesses the likelihood of the null hypothesis of no correlation among the variables considered for factor analysis. The null hypothesis

implies that every variable correlates poorly or not at all with all other variables, and all variables are entirely independent. Given that factor analysis aims to identify underlying patterns of correlation among variables measuring similar things, a scenario of no correlation (null hypothesis) would be problematic. If no variables correlate, there are no hidden patterns to find, indicating that the considered sample is not suitable for factor analysis. Therefore, Bartlett's test, measuring the probability of the null hypothesis of no correlation, should approach 0, **making p-values < 0.05 acceptable**.

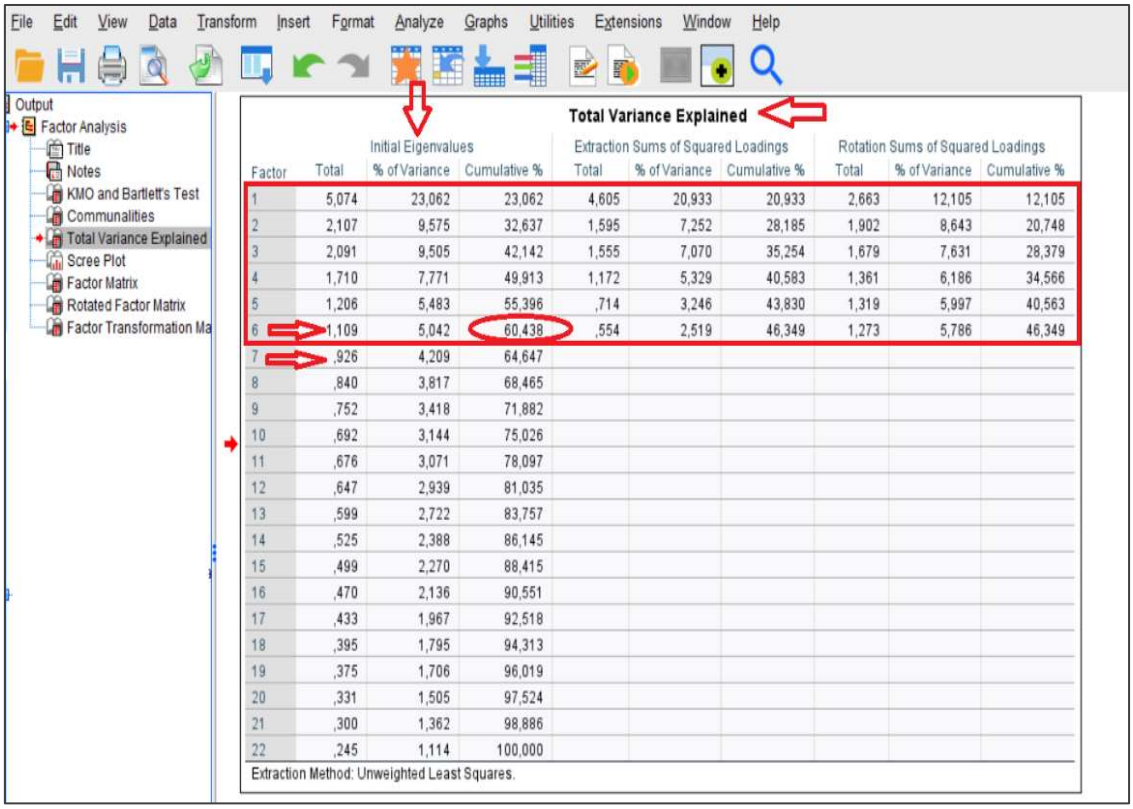
Also in this case, the output shown in Fig. 14 provide evidence of good Bartlett's sphericity values.

The satisfactory results of both statistical parameters suggest that you can proceed with your Factor Analysis.

Moving on to the third piece of information available in the output (temporarily skipping the communality table): 'Total Variance Explained' (varianza totale spiegata) (Fig. 15).

In this table, we observe 22 factors extracted, yet we only consider the first 6 as they align with our settings, having an eigenvalue >1 (i.e., each factor explains the variability of at least 1 original variable). These initial six factors collectively account for over 60% (60.438) of the variance. While acceptable, this percentage suggests a somewhat modest explanation, indicating a potential need for refining the factorial model by eliminating variables.

Figure 15. *The total explained variance*



Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,074	23,062	23,062	4,605	20,933	20,933	2,663	12,105	12,105
2	2,107	9,575	32,637	1,595	7,252	28,185	1,902	8,643	20,748
3	2,091	9,505	42,142	1,555	7,070	35,254	1,679	7,631	28,379
4	1,710	7,771	49,913	1,172	5,329	40,583	1,361	6,186	34,566
5	1,206	5,483	55,396	,714	3,246	43,830	1,319	5,997	40,563
6	1,109	5,042	60,438	,554	2,519	46,349	1,273	5,786	46,349
7	,926	4,209	64,647						
8	,840	3,817	68,465						
9	,752	3,418	71,882						
10	,692	3,144	75,026						
11	,676	3,071	78,097						
12	,647	2,939	81,035						
13	,599	2,722	83,757						
14	,525	2,388	86,145						
15	,499	2,270	88,415						
16	,470	2,136	90,551						
17	,433	1,967	92,518						
18	,395	1,795	94,313						
19	,375	1,706	96,019						
20	,331	1,505	97,524						
21	,300	1,362	98,886						
22	,245	1,114	100,000						

Extraction Method: Unweighted Least Squares.

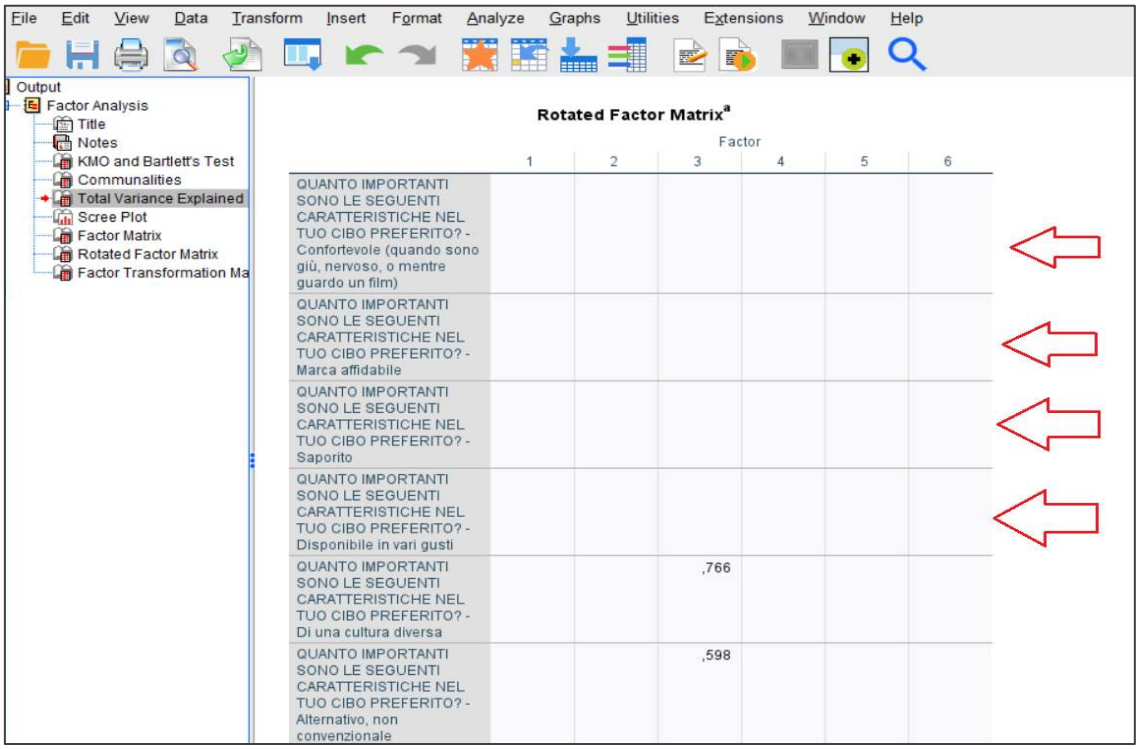
Below the table, a screeplot illustrates the relationship among the factors. Notably, all first 6 factors overcome the eigenvalue of **1**.

Figure 16. *Screeplot of the Extracted Factors*

This factor solution appears somewhat weak. Moreover, there is minimal inclination between F2 and F3, as well as between F5 and F6, suggesting the presence of redundancy and overlapping dimensions. This implies that the information captured by one factor is already accounted for by another factor or factors, indicating a lack of unique contribution to the understanding of the underlying data structure. Considering a more parsimonious structure with 5 factors (or even fewer), we may attain a more optimal solution.

When examining the values displayed in the matrix of rotated factors, it becomes apparent that certain variables, such as 'confortevole' (comfort), 'marca affidabile' (reliable brand), 'saporito' (tasty) or 'disponibile in vari gusti,' (available in various flavours) exhibit empty rows (Fig. 17).

Figure 17. *Matrix of rotated factors and loading coefficients*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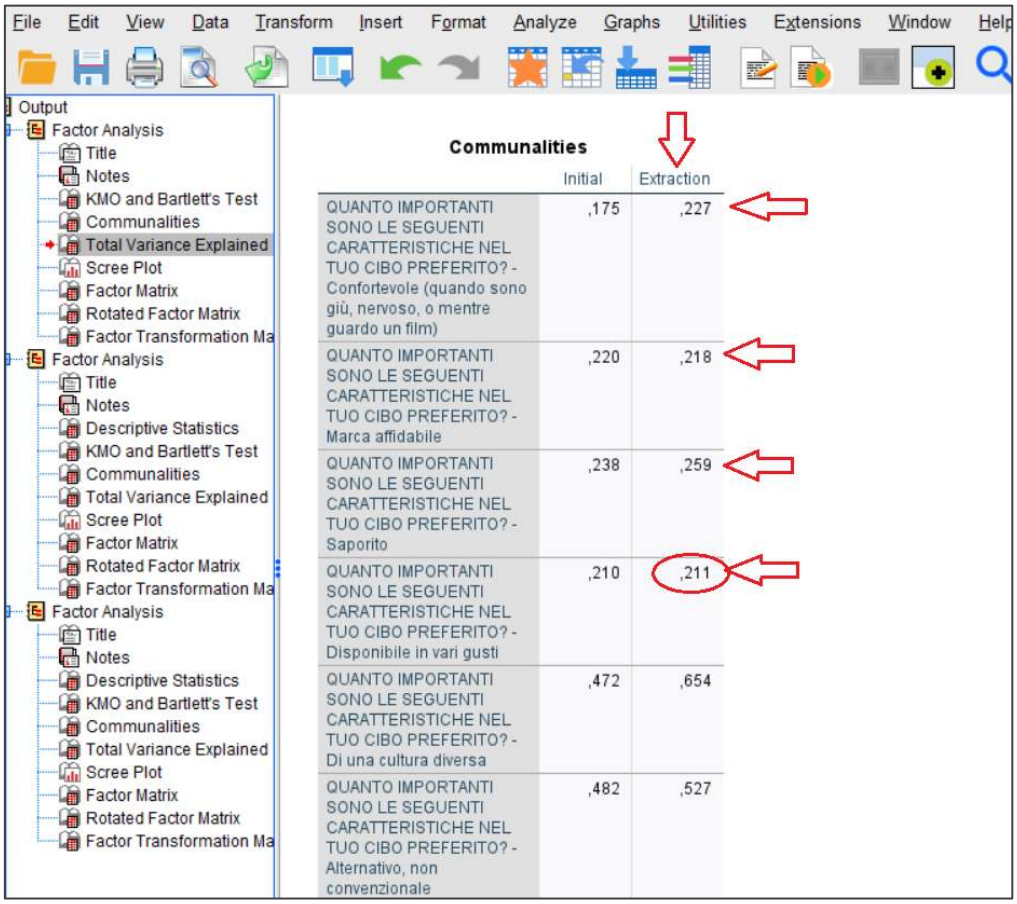
1 2 3 4 5 6
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Confortevole (quando sono giù, nervoso, o mentre guardo un film)
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Marca affidabile
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Saporito
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Disponibile in vari gusti
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa
,766
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale
,598

However, these rows are not truly empty; they appear blank because you have chosen to 'eliminate loading coefficients lower than 0.50' in your settings. This indicates that these variables, entirely represented by blank cells, possess correlation values lower than 0.5 with all six factors. Such variables are deemed redundant as they do not significantly contribute to any single factor, making them weak candidates for elimination in the process of refining the factor structure. Keep in mind that loading coefficients higher than 0.5 indicate a stronger correlation between the variable and the factor, whereas values lower than 0.5 indicate a weaker correlation between the variable and the factor.

To enhance the factorial structure, we need to eliminate weakly correlated variables. But how many should we eliminate, and which ones should we start with? To make this decision, refer to the table of rotated factors and compare it with the communalities table ('comunalità') (Fig. 18). This involves going back to the second piece of information in the output (which I suggested skipping momentarily) and checking the column of extracted values. Communality reflects how much variance variables share with all extracted factors. In simpler terms, it indicates the extent to which the extracted factors explain the variance of each original variable. Communality values range from 0 to 1, with higher values (higher than 0.5) suggesting a stronger association between the variable and the extracted factors.

Figure 18. *Communalities table*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Factor Matrix
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Factor Transformation Ma
Communalities
Initial Extraction
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Confortevole (quando sono giù, nervoso, o mentre guardo un film) ,175 ,227
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Marca affidabile ,220 ,218
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Saporito ,238 ,259
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Disponibile in vari gusti ,210 ,211
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa ,472 ,654
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale ,482 ,527

As explained in Chapter 2, generally, variables with low communalities align with those exhibiting low loading factors in the rotated matrix table. Occasionally, during the variable elimination steps, variables with lower communalities may not correspond to

variables with loading factors below 0.5. In such cases, the decision on which variable to eliminate falls entirely on the researcher, guided by their research goals and theoretical assumptions. However, in general, the values of communalities should take precedence over loading factor values in informing the decision. Over time, variables with low communalities typically prove to be weak in the rotated matrix table throughout the elimination process.

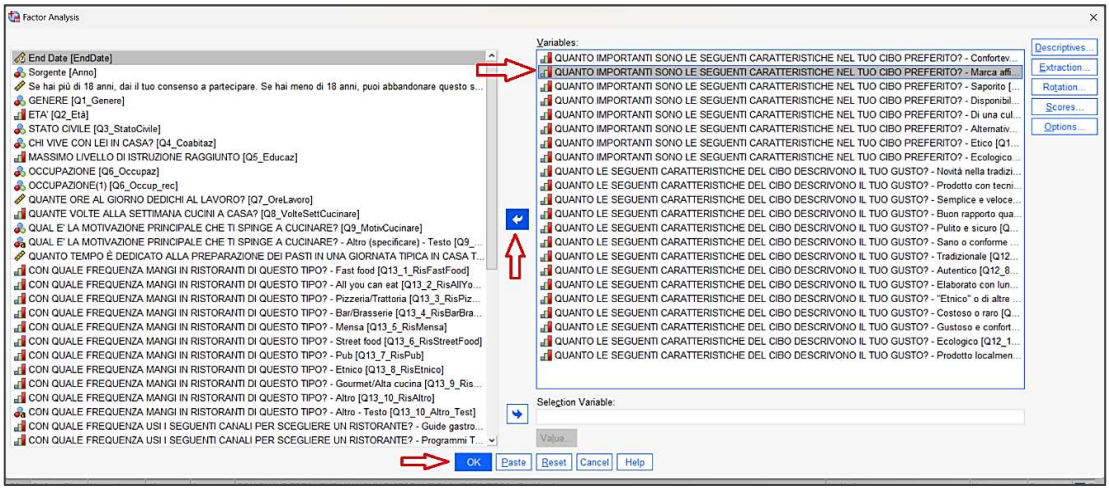
Variable elimination is a stepwise process, where variables are eliminated on-by-one based on a backward elimination strategy. The process is backward, because to decide which variable to eliminate first, we have to go back to the communality table, confront values with those of rotated factors, eliminate the variable with lowest factor, launch again factor analysis. When a new output opens, you should repeat this backward elimination one-by-one, until the optimal factor solution is reached. Optimal factor solution means that: there are no blank rows in the factor of rotated matrix (meaning that all variables load at least more that 0.5 to one factor) and in the communalities table values are all about 0.5.

The first variable I need to eliminate is the one with the lowest communality value, which, in this case, is 'disponibile in vari gusti' (available in various flavors) with a communality value of 0.211 (Fig. 18). I begin the elimination process and, following a stepwise approach, launch the factor analysis again to generate a new output. First step is navigate back to my dataset, access variable views, identify the name of the variable (in this case, variable Q11_4_VariGusti)

There are two methods for eliminating variables:

1. Navigate to the variable views page. From the menu bar, select ‘Analyze’ (analizza) >> ‘Dimension reduction’ (riduzione delle dimensioni) >> ‘Factor’ (fattore). Choose the variable to eliminate in the right box and click the arrow to move it back to the left box. Click 'OK' to confirm and relaunch the settings (Fig. 19).

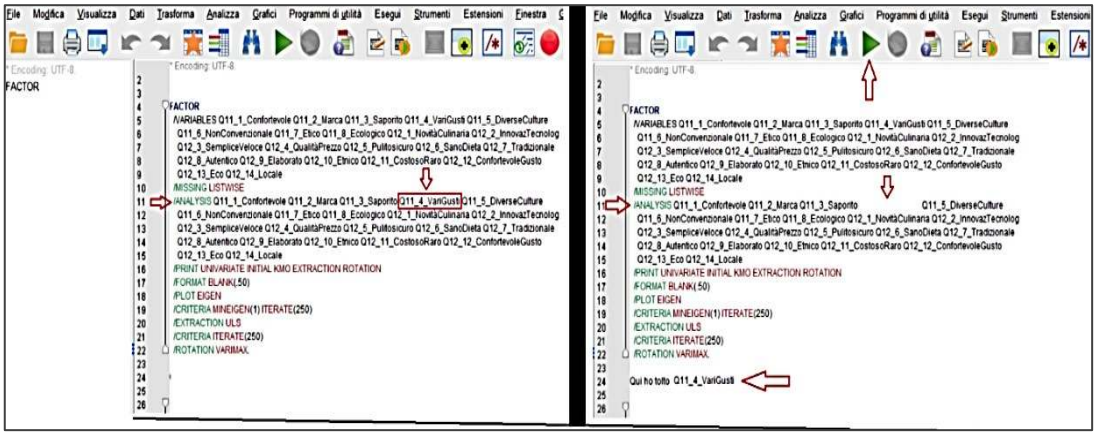
Figure 19. *Variable elimination from the settings menu*



2. If you created a syntax sheet, go to your syntax and remove this variable from the “analysis” section. "Be careful not to remove it from the above section but only from 'analysis.' To track your operations, cut the variable you decide to eliminate and paste it under your syntax to document the sequence of eliminations (as shown in Fig. 20, where you can note 'I eliminated Q11_4_Varigusti'). Then, select your new syntax and

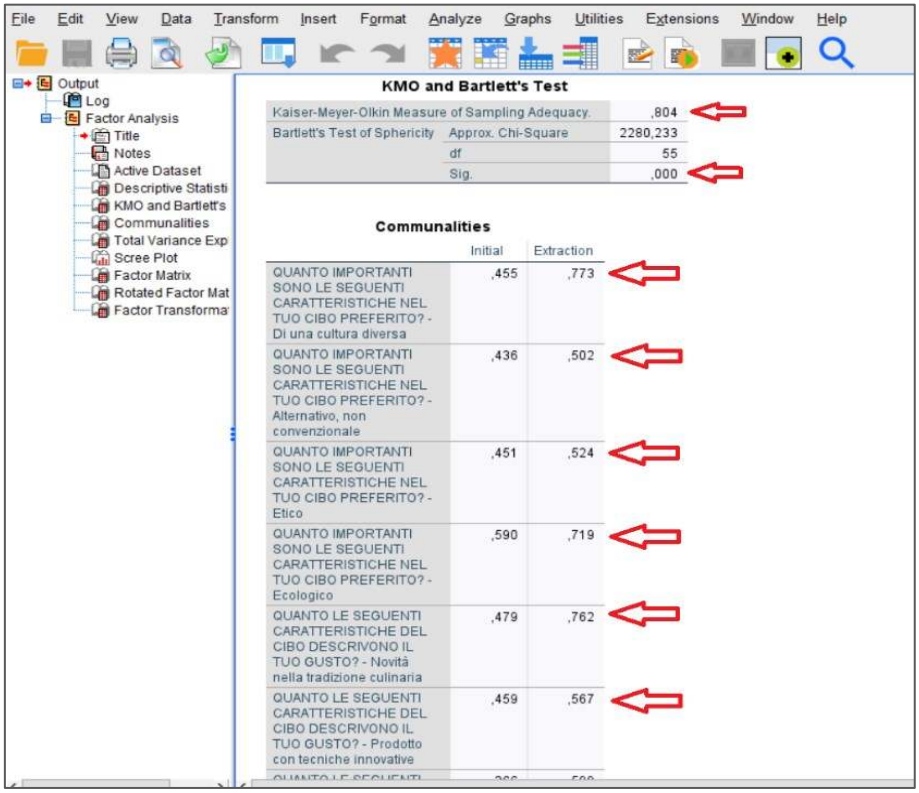
execute it. In both cases, a new factor solution appears in the output file, illustrating the impact of the variable elimination. Repeat this process until the optimal factor solution is achieved (see Fig. 20).

Figure 20. *Variable elimination from syntax*


File Modifica Visualizza Dati Trasforma Analizza Grafici Programmi di utilità Esegui Strumenti Estensioni
FACTOR
/VARIABLES Q11_1_Confortevole Q11_2_Marca Q11_3_Saporito Q11_4_VariGusti Q11_5_DiverseCulture
Q11_6_NonConvenzionale Q11_7_Etico Q11_8_Ecologico Q12_1_NovitàCulinaria Q12_2_InnovazTecnolog
Q12_3_SempliceVeloce Q12_4_QualitàPrezzo Q12_5_Pulitosicuro Q12_6_SanoDieta Q12_7_Tradizionale
Q12_8_Autentico Q12_9_Elaborato Q12_10_Etnico Q12_11_CostosoRaro Q12_12_ConfortevoleGusto
Q12_13_Eco Q12_14_Locale
MISSING LISTWISE
/ANALYSIS Q11_1_Confortevole Q11_2_Marca Q11_3_Saporito Q11_4_VariGusti Q11_5_DiverseCulture
/PRINT UNIVARIATE INITIAL KMO EXTRACTION ROTATION
/FORMAT BLANK(50)
/PLOT EIGEN
/CRITERIA MINEIGEN(1) ITERATE(250)
/EXTRACTION ULS
/CRITERIA ITERATE(250)
/ROTATION VARIMAX.
Qui ho tolto Q11_4_VariGusti

You'll generate a new output. Check all parameters again and repeat this operation, eliminating one variable with the lowest communality step by step until you reach a situation where there are no blank lines in the rotated factors matrix, and all variables show a loading coefficient value of at least > 0.5 with one factor (indicating they are well represented by that factor). This is our assumption of the optimal solution: each variable has a high correlation (>0.5) with only one factor and minimal correlations (made invisible) with other factors, signifying that it is uniquely explained by that factor. Remember, overlapping situations are not desirable in factor analysis.

Figure 21. *Statistic output of the factor optimal solution*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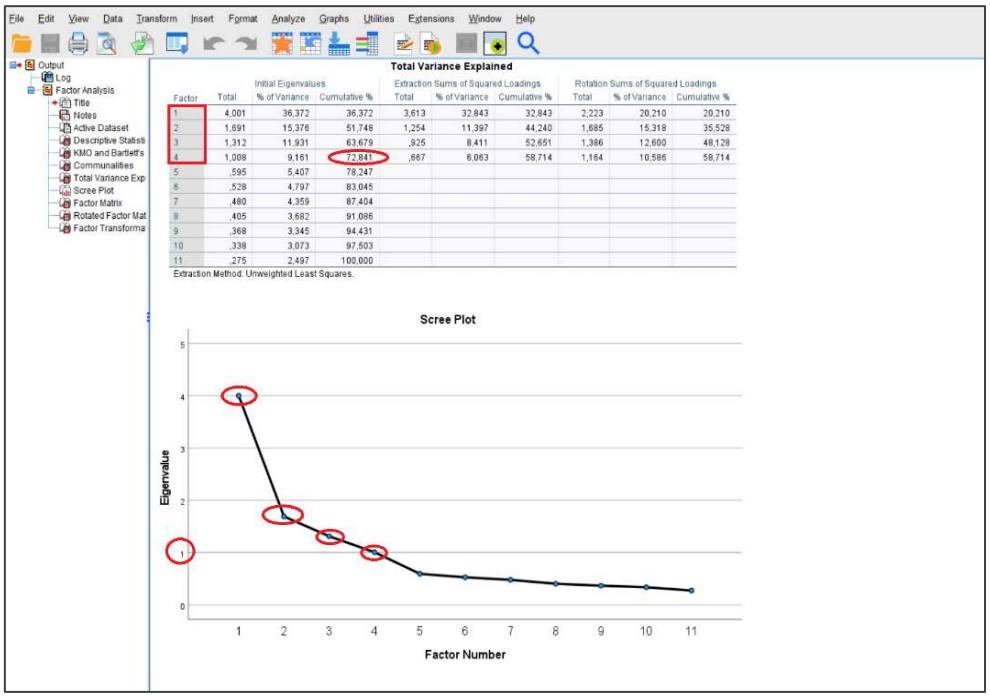
KMO and Bartlett's Test
Kaiser-Meyer-Olkin Measure of Sampling Adequacy. ,804
Bartlett's Test of Sphericity Approx. Chi-Square 2280,233
df 55
Sig. ,000
Communalities
Initial Extraction
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa ,455 ,773
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale ,436 ,502
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico ,451 ,524
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Ecologico ,590 ,719
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Novità nella tradizione culinaria ,479 ,762
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto con tecniche innovative ,459 ,567

In this specific case, our best solution consists of 4 factors, 11 variables, KMO = 0.804; Bartlett p-value < 0.001, all communality values higher than 0.5 (Fig. 21). These four factors collectively explain 72.841% (73%) of the variance, with the first factor contributing significantly to the majority of this variance, a trend also depicted in the scree plot (Fig. 22).

Figure 22. *The total explained variance and the screeplot of the optimal factor solution*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Factor Transforma
Total Variance Explained
Initial Eigenvalues
Extraction Sums of Squared Loadings
Rotation Sums of Squared Loadings
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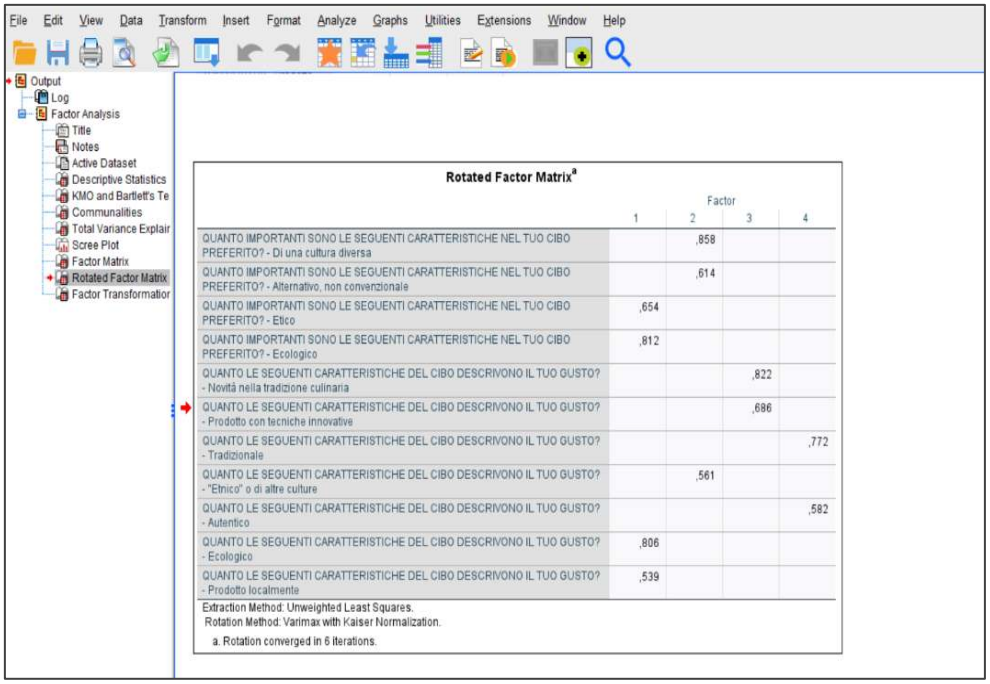
1 4,001 36,372 36,372 3,613 32,843 32,843 2,223 20,210 20,210
2 1,691 15,376 51,748 1,254 11,397 44,240 1,685 15,318 35,528
3 1,312 11,931 63,679 ,925 8,411 52,651 1,386 12,600 48,128
4 1,008 9,161 72,841 ,667 6,063 58,714 1,164 10,586 58,714
5 ,595 5,407 78,247
6 ,528 4,797 83,045
7 ,480 4,359 87,404
8 ,405 3,682 91,086
9 ,368 3,345 94,431
10 ,338 3,073 97,503
11 ,275 2,497 100,000
Extraction Method: Unweighted Least Squares.
Scree Plot
Eigenvalue
Factor Number

The four factors also appear as clearly distinguishable in the rotated factor matrix (Fig. 23).

Figure 23. *Rotated factor matrix of the factor optimal solution*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Rotated Factor Matrix[a]
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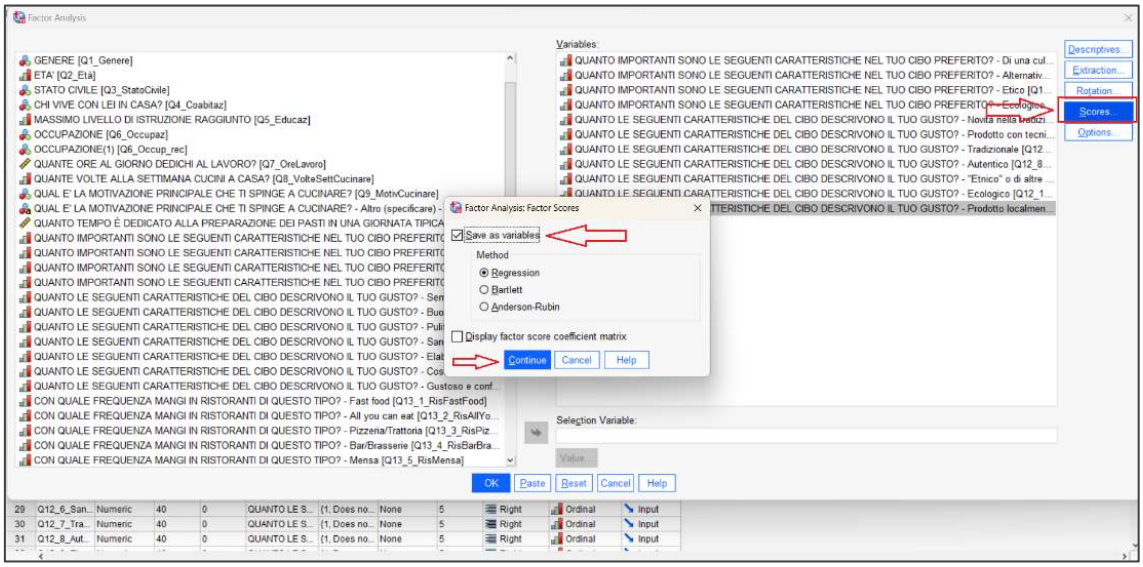
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa ,858
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale ,614
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico ,654
QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Ecologico ,812
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Novità nella tradizione culinaria ,822
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto con tecniche innovative ,686
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Tradizionale ,772
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - "Etnico" o di altre culture ,561
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Autentico ,582
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Ecologico ,806
QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto localmente ,539
Extraction Method: Unweighted Least Squares.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

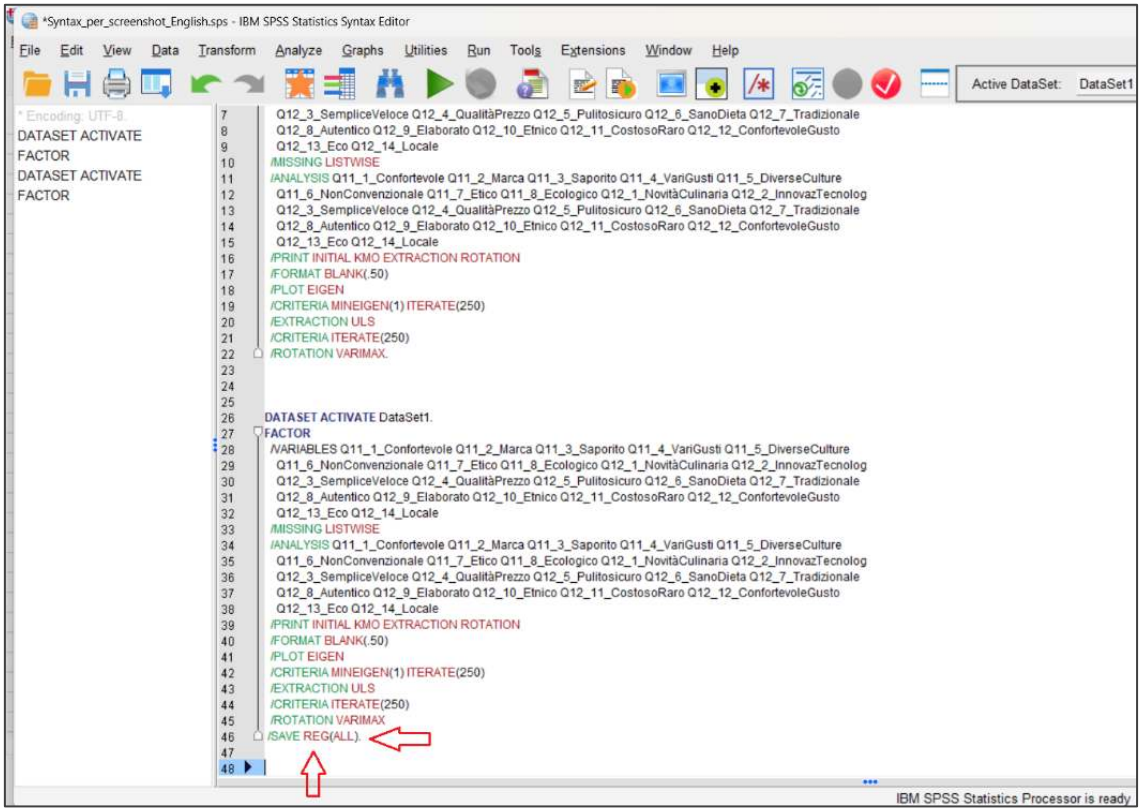
Only at this stage can we save our extracted factors as variables in our dataset, a step that we skipped in the initial settings. Navigate back to the main menu, click on ‘scores’ (punteggi), check ‘save as variables’ (salva come variabili), proceed by clicking 'continue' (continua), and then finalize by clicking 'OK'.

Figure 24. *Save factors as variables*



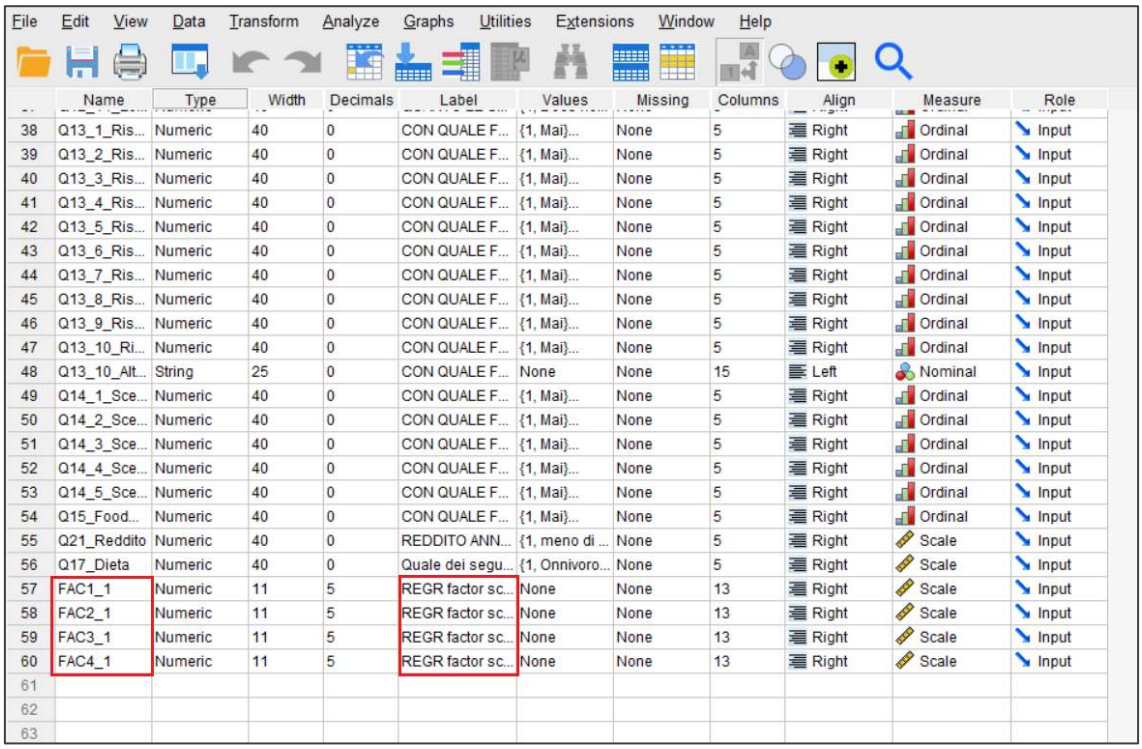
Now, the factors have been saved as variables. To access them, go to your dataset's 'Variable View' ('Vista Variabili') page, where you will find the four factors located at the bottom. In your syntax, these settings appear as the string '/SAVE REG(ALL).' (Fig. 25)

Figure 25. *Save factors as variables in the syntax*



In the 'Variable View' page, the saved factors will appear at the very bottom of your dataset (Fig. 26).

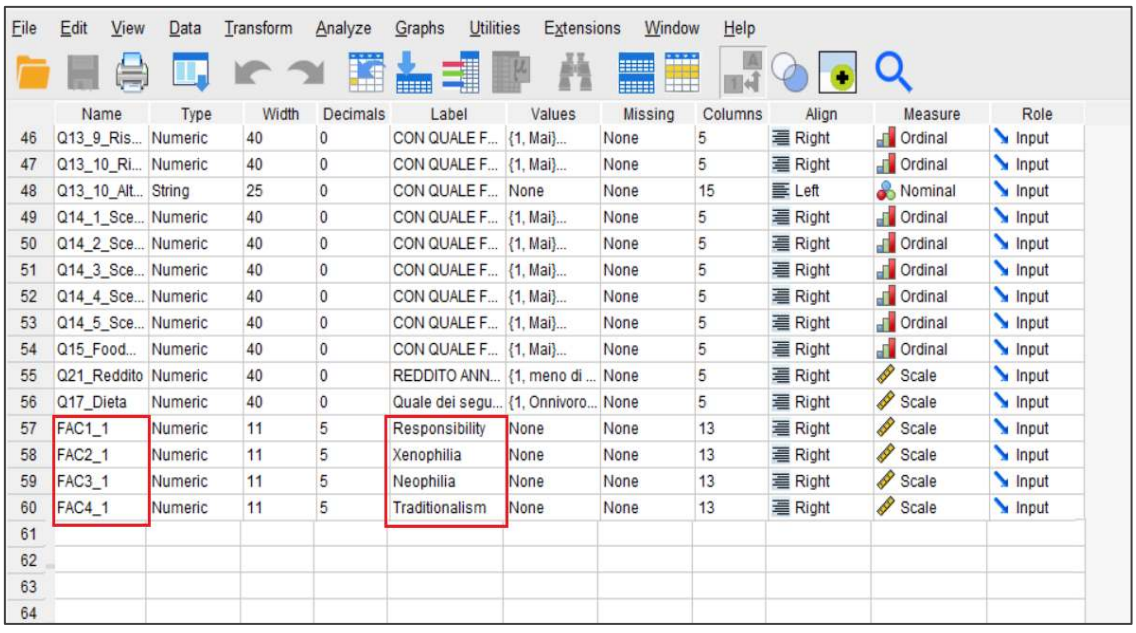
Figure 26. *Factors saved as variables in the dataset*



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
38	Q13_1_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
39	Q13_2_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
40	Q13_3_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
41	Q13_4_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
42	Q13_5_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
43	Q13_6_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
44	Q13_7_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
45	Q13_8_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
46	Q13_9_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
47	Q13_10_Ri...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
48	Q13_10_Alt...	String	25	0	CON QUALE F...	None	None	15	Left	Nominal	Input
49	Q14_1_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
50	Q14_2_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
51	Q14_3_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
52	Q14_4_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
53	Q14_5_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
54	Q15_Food...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
55	Q21_Reddito	Numeric	40	0	REDDITO ANN...	{1, meno di ...	None	5	Right	Scale	Input
56	Q17_Dieta	Numeric	40	0	Quale dei segu...	{1, Onnivoro...	None	5	Right	Scale	Input
57	FAC1_1	Numeric	11	5	REGR factor sc...	None	None	13	Right	Scale	Input
58	FAC2_1	Numeric	11	5	REGR factor sc...	None	None	13	Right	Scale	Input
59	FAC3_1	Numeric	11	5	REGR factor sc...	None	None	13	Right	Scale	Input
60	FAC4_1	Numeric	11	5	REGR factor sc...	None	None	13	Right	Scale	Input
61											
62											
63											

The next step is to give a name to these factors. To do that, we have to go back to the rotated factor matrix and see which variables are correlated to each factor and how they describe them. Accordingly, we choose a definition that describes the hidden consumer pattern expressed by those behavioral variables. You can directly overwrite the name of each factor in the corresponding label box on the variable view page (Fig. 27).

Figure 27. *Naming extracted factors*

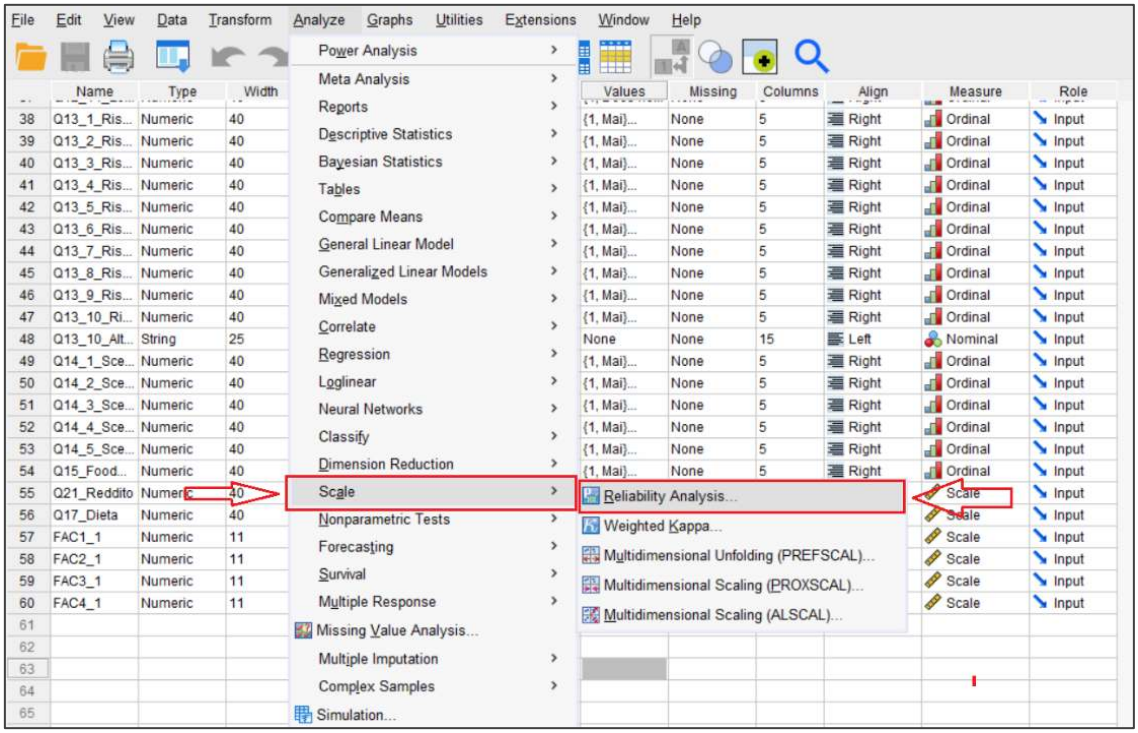


	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
46	Q13_9_Ris...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
47	Q13_10_Ri...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
48	Q13_10_Alt...	String	25	0	CON QUALE F...	None	None	15	Left	Nominal	Input
49	Q14_1_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
50	Q14_2_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
51	Q14_3_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
52	Q14_4_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
53	Q14_5_Sce...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
54	Q15_Food...	Numeric	40	0	CON QUALE F...	{1, Mai}...	None	5	Right	Ordinal	Input
55	Q21_Reddito	Numeric	40	0	REDDITO ANN...	{1, meno di ...	None	5	Right	Scale	Input
56	Q17_Dieta	Numeric	40	0	Quale dei segu...	{1, Onnivoro...	None	5	Right	Scale	Input
57	FAC1_1	Numeric	11	5	Responsibility	None	None	13	Right	Scale	Input
58	FAC2_1	Numeric	11	5	Xenophilia	None	None	13	Right	Scale	Input
59	FAC3_1	Numeric	11	5	Neophilia	None	None	13	Right	Scale	Input
60	FAC4_1	Numeric	11	5	Traditionalism	None	None	13	Right	Scale	Input
61											
62											
63											
64											

If you want to check the reliability of the scales correlated to each pattern, you can measure Cronbach Alpha per each pattern of variables. Cronbach's Alpha is a measure of internal consistency reliability. Its values typically range from 0 to 1 (Cronbach, 1951). Higher values, closer to 1, indicate higher internal consistency.

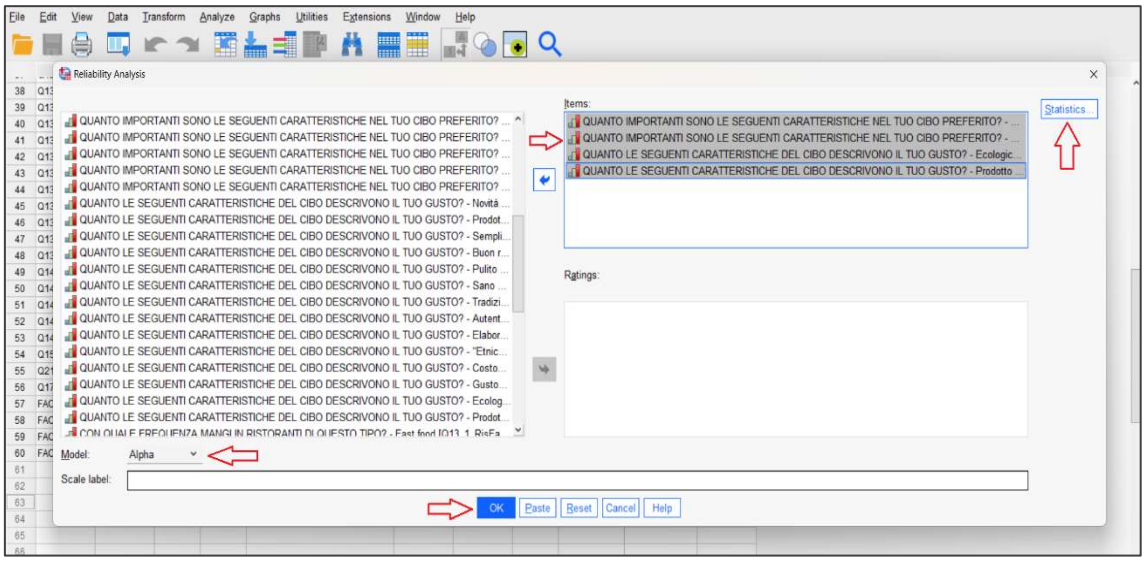
To measure Cronbach's Alpha, go to the 'Variable View,' then click on 'Analyze' >> 'Scale' >> 'Reliability Analysis' (Fig. 28).

Figure 28. *Settings for assessing reliability of the scale variables correlated to each factor*



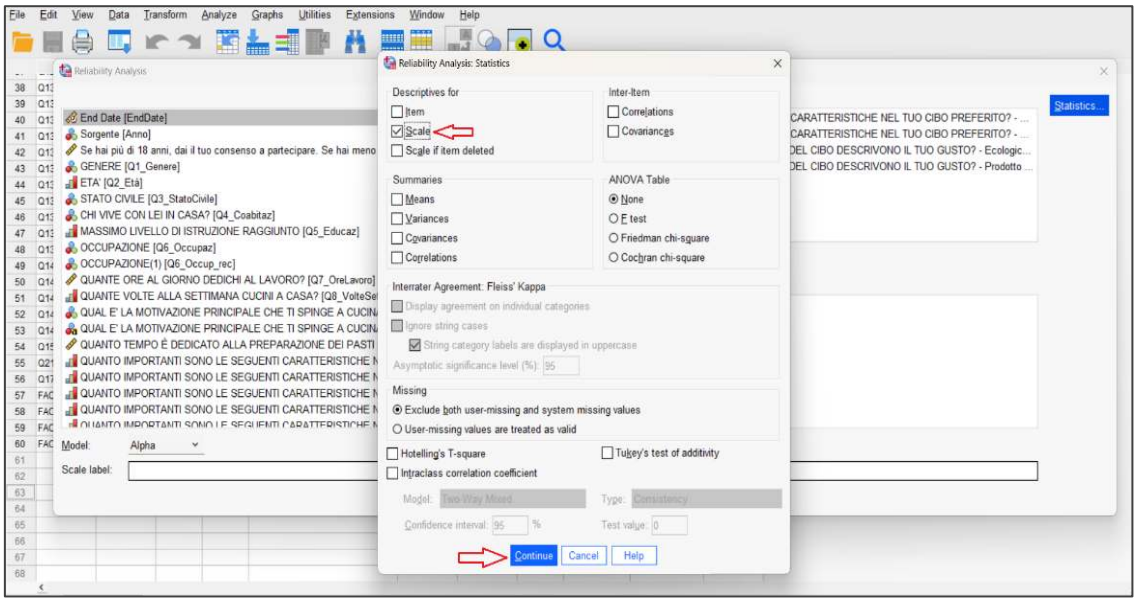
A menu opens, move on the right box the variables that are correlated to the first factor (Fig. 29). Below, you fill find selected "Alpha" as default method to assess scale reliability. Keep it as it is. Then click on the button 'statistics' on the right side.

Figure 29. *Settings for Cronbach's Alpha measure*



Another menu opens, select 'scale', and than click on continue, and then OK (Fig. 30).

Figure 30. *Further settings for Cronbach's Alpha measure*



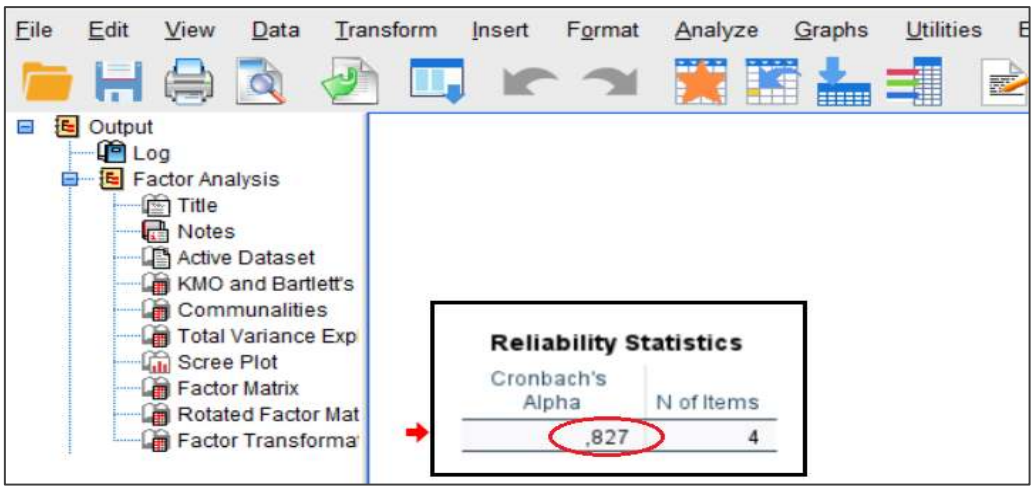
In your output you'll obtain a Cronbach's Alpha value assessing the reliability of the scale variables in this case correlated to factor 1 'Responsibility'.

Literature provides thresholds to decide Cronbach's alpha acceptability, usually classified as follows (Kline, 1999; Nunnally, 1978: 245):

- Below 0.6: Generally considered low reliability.
- 0.6 to 0.7: Moderate reliability.
- 0.7 to 0.8: Good reliability.
- 0.8 and above: Excellent reliability.

In this case, the output shows an excellent value of reliability, equal to 0.827 (Fig. 31). These values further confirm the robustness of our factor analysis.

Figure 31. *Cronbach's Alpha measure assessing the scale reliability of Factor 1.*



Repeat the Cronbach's Alpha measure for all other groups of scale variables correlated to the remaining factors. This provides a comprehensive assessment of reliability across all factors.

That's all!

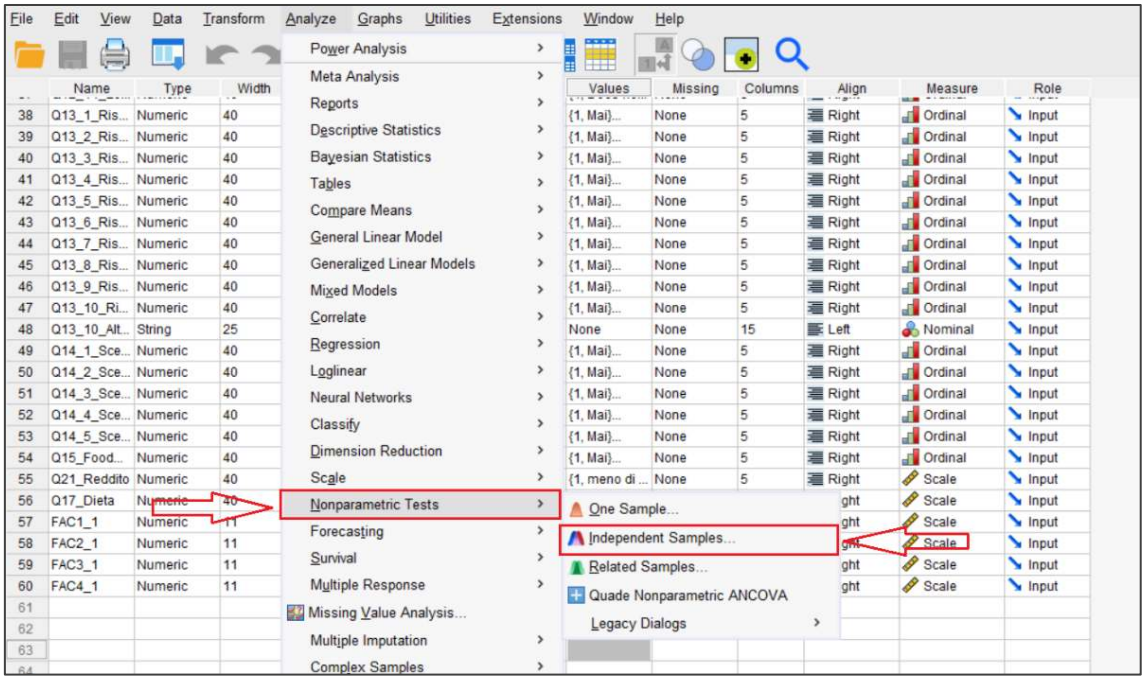
3.4.3. How do these factors distribute among the surveyed population? Do they exhibit variations based on the personal characteristics of respondents?

In sociological or marketing terms, it is interesting to see how these factors (hidden patterns driving consumer behaviors) distribute among respondents based on their sociodemographic or lifestyle characteristics.

In terms of data analysis, you should check if crossing these factor variables with variables like gender, age, dietary styles, and so on, reveals statistically significant differences among these groups of respondents.

To do that, go back to variable views, click again on Analyze >> then click non-parametric tests >> independent samples (Fig. 32). You are asking the program to compare the distribution of these factor variables among independent age or gender sub-samples of populations. These sub-samples are independent because being male or female, or being a Millennial or a Baby Boomer, are characteristics independent of each other.

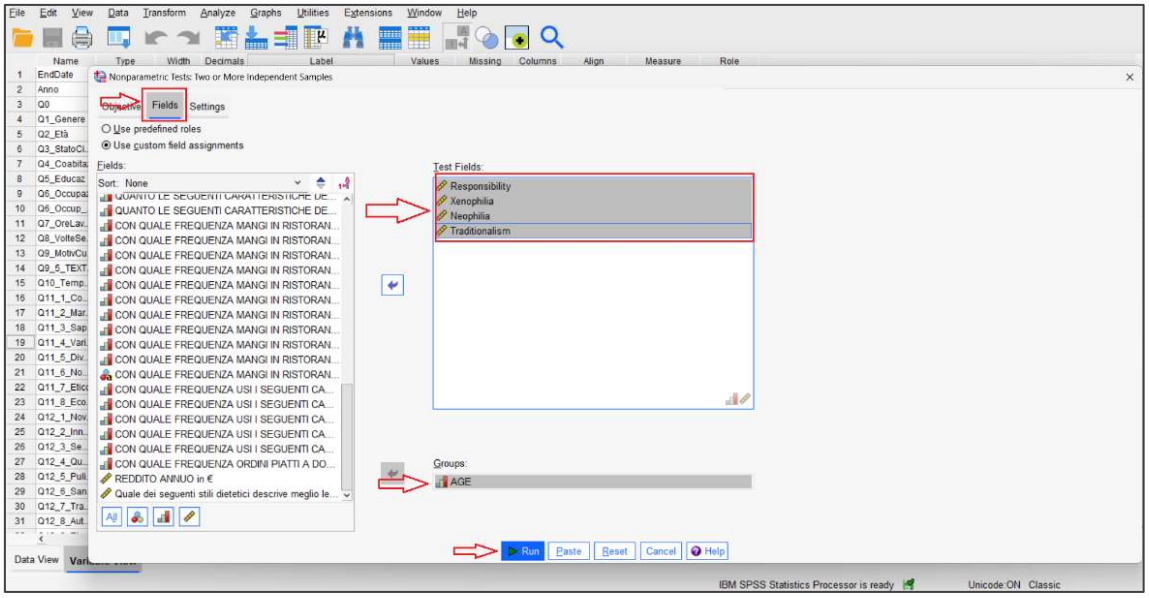
Figure 32. *Settings to compare factors across respondents' socio-demographic characteristics*



A menu opens. Navigate to the 'Fields' section, move the variables you have chosen as your fields to test (in this case, your factor variables) under the box labeled 'Test Fields' on the right side (Fig. 33). Similarly, select the variable 'age' from the left box and transfer it to the 'Groups' box on the right. The sub-groups you want to compare are distinguished by age.

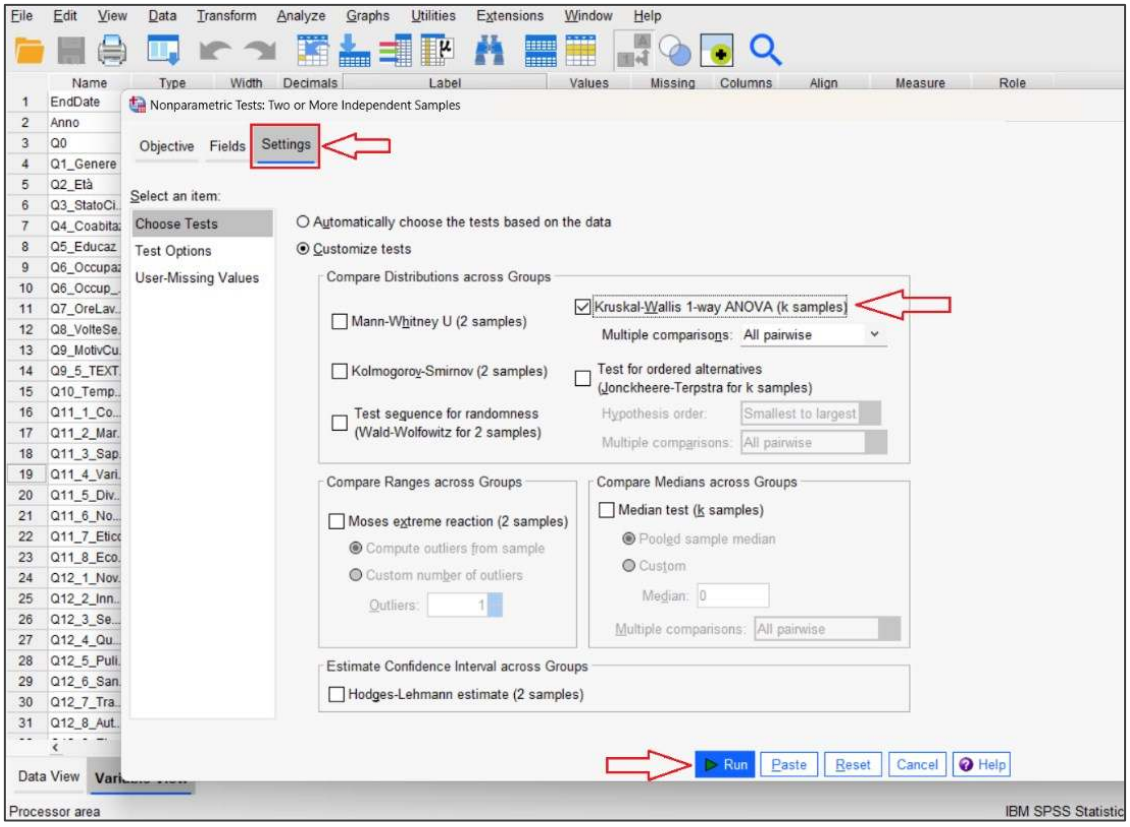
Then click on 'run' (esegui) to proceed.

Figure 32. *Settings to compare factors across respondents' gender characteristics*



Finally, you need to decide which test to use to assess statistically significant differences among the groups being compared. Click on 'impostazioni' (settings), modify the default settings, and opt for personalization (Fig. 33). The most suitable solution for this type of data is the 'Kruskal Wallis' One-way ANOVA by k samples (where k represents the number of sub-groups being compared, such as different age ranges). Click on 'esegui' (execute) to proceed.

Figure 33. *Setting the Kruskal-Wallis non-parametric test for comparing factor variables across sub-samples*

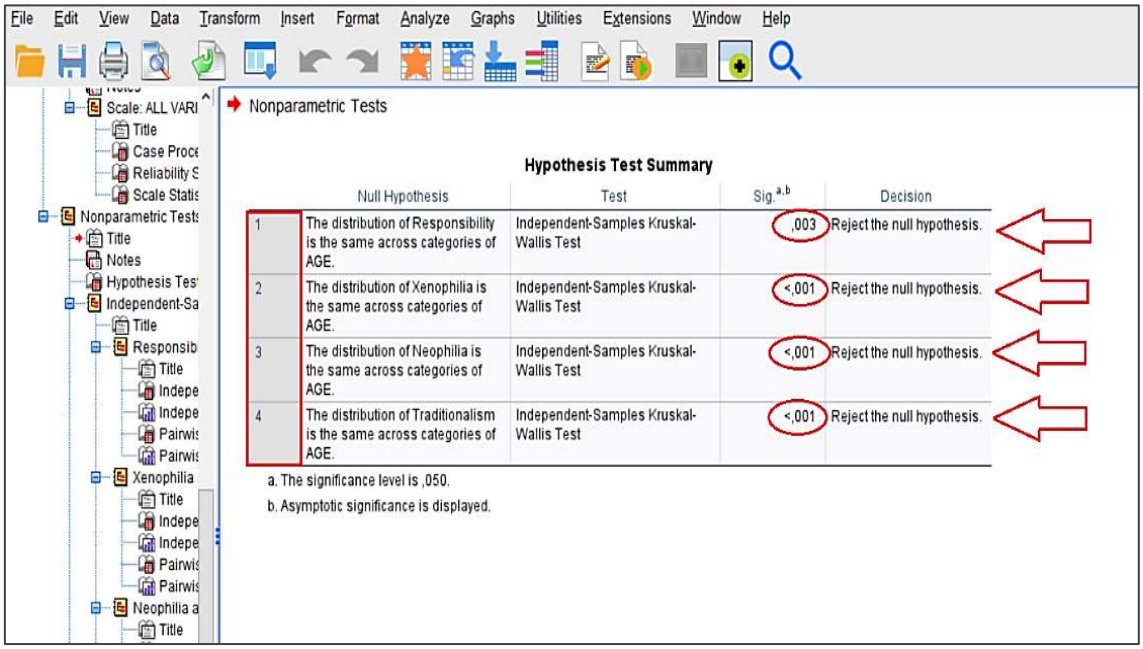


An output will appear with the null hypothesis of no difference for each factor among age groups on the left, the significance value calculated through the Kruskal-Wallis test, and the final decision to either reject or accept the null hypothesis based on the significance value.

In this case, the significance value (p-value) is very close to zero for all four factors. This indicates that there is almost no chance (sig. < 0.05) that the null hypothesis, suggesting no difference in the distribution of factors across respondents' age groups, is true. Thus, the null hypothesis is rejected, implying a statistical difference in these factor variables based on respondents' age.

In sociological terms, this suggests that the hidden patterns of values and motivations driving the observed population's behaviors are expected to differ significantly according to respondents' age. Individuals belonging to different age groups are likely to exhibit distinct hidden patterns.

Figure 34. *Output of factors' comparison across age-groups through Kruskal-Wallis test*


File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help
Nonparametric Tests
Hypothesis Test Summary
Null Hypothesis
Test
Sig.a,b
Decision
1 The distribution of Responsibility is the same across categories of AGE. Independent-Samples Kruskal-Wallis Test ,003 Reject the null hypothesis.
2 The distribution of Xenophilia is the same across categories of AGE. Independent-Samples Kruskal-Wallis Test <,001 Reject the null hypothesis.
3 The distribution of Neophilia is the same across categories of AGE. Independent-Samples Kruskal-Wallis Test <,001 Reject the null hypothesis.
4 The distribution of Traditionalism is the same across categories of AGE. Independent-Samples Kruskal-Wallis Test <,001 Reject the null hypothesis.
a. The significance level is ,050.
b. Asymptotic significance is displayed.

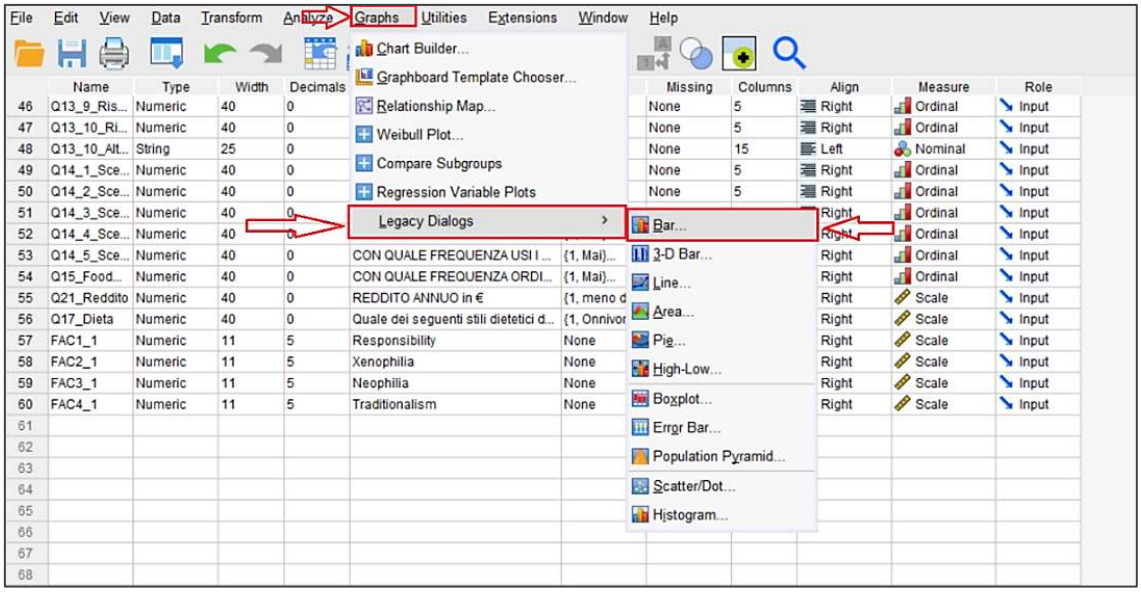
Repeat this test for all relevant personal variables, whether they are socio-demographic, such as gender or education, or lifestyle-related, such as dietary styles or time devoted to cooking. This helps associate these different factors with various target populations.

3.4.4. Graphic Visualization of the Extracted Factors

Especially in the field of marketing and more broadly in the social sciences, it is crucial to present these statistical outputs in a clear and easily understandable manner. The use of simple graphs, such as bar charts, is an effective way to communicate the results in an immediate and intuitive manner.

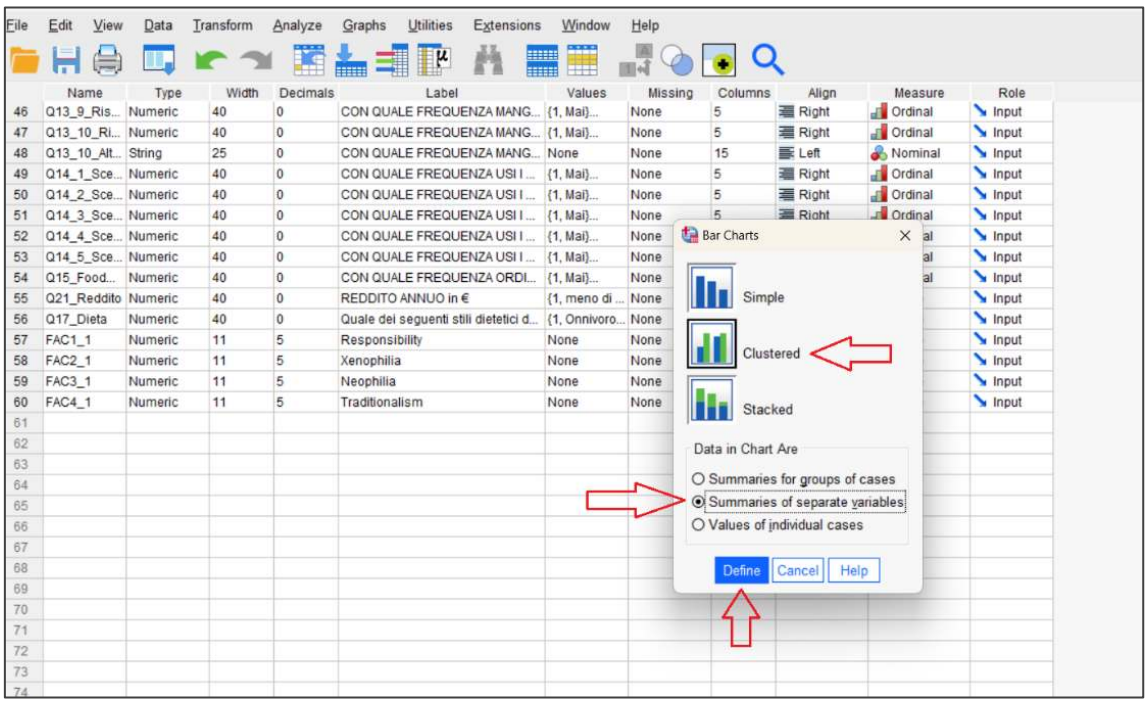
To do that, navigate to your dataset, go to variable views, and on the menu bar, select 'Graphs' (Grafici) >> 'Legacy dialogs' (finestre di legacy) >> 'Bar' (barra), as shown in Fig. 35.

Figure 35. *Settings for visualizing results through a bar chart*



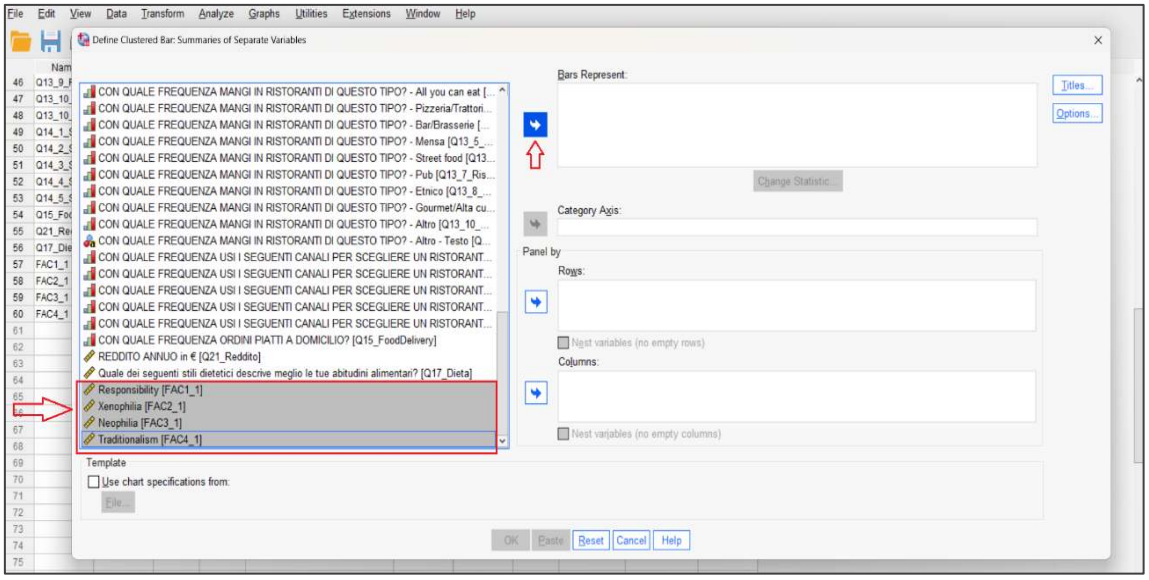
Select 'Bar chart' (grafico a barre) and then click on 'Clustered' (Raggruppato), indicating that you want to see variables clustered by groups. Choose 'Summaries of distinct variables' (riepiloghi di variabili distinte), signifying that your bars will represent distinct variables, in this case, factor variables (Fig. 36). Finally, click on 'Define' (definisci) to proceed.

Figure 36. *Settings to customize the desired bar-chart*



A menu opens; select the four factors in the box on the left and move them to the right box under 'le barre rappresentano' (bars represent) because the bars of the graph represent the factors. In this way, you are instructing the program that in the bar chart you're creating, the bars represent the factor variables (Fig. 37).

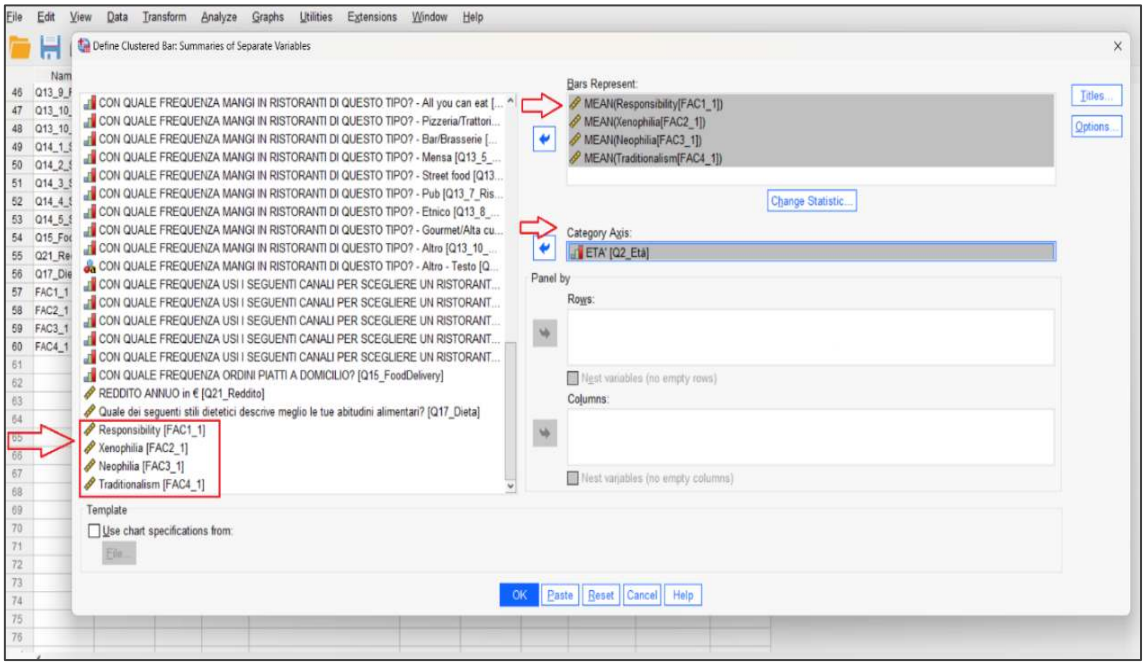
Figure 37. *Settings to decide which variables to represent in the bar-chart.*



While moving the factor variables from the left to the right box, the program will automatically calculate and show the mean values of these variables (Fig. 38).

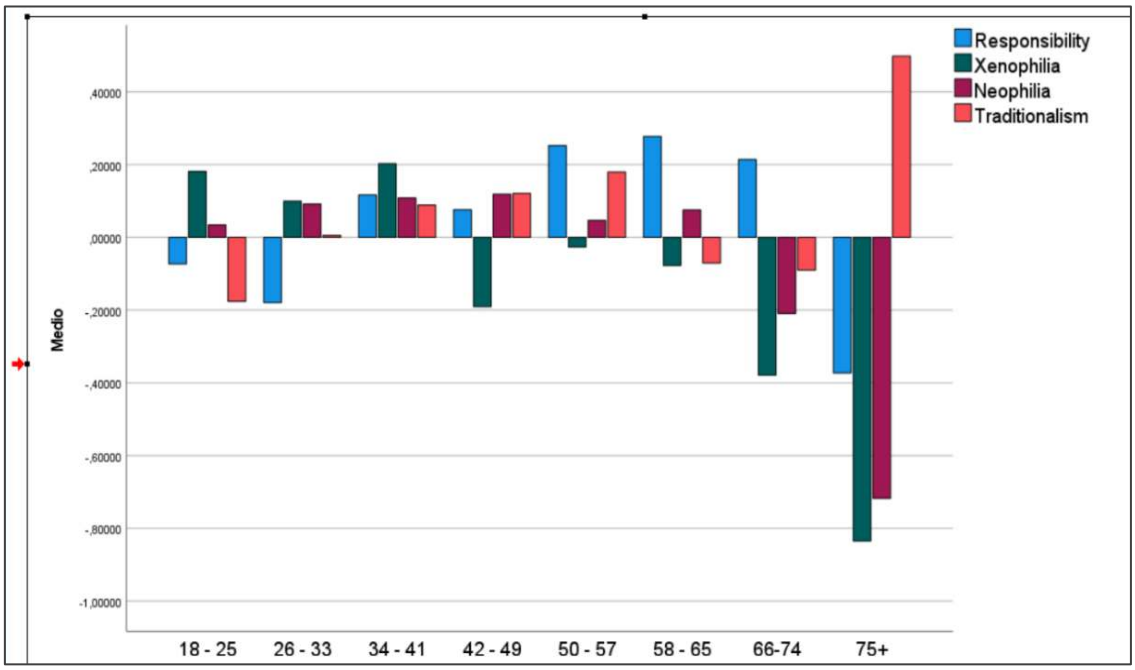
Likewise, decide which variable you want put in the box 'Category Axis' (asse delle categorie). In general, as being the category-axis the one representing independent variables, it generally represents characteristics that are assumed as independent, input personal characteristics, such as gender, age, income, or even lifestyle features, such as dietary pattern. This is the variable you want to cross with factors to visualize how they do distribute. In this specific case, under the axes of categories, put the variable age because, following the previous findings proving that factors distribute in a significantly different way across various age groups, it is interesting to visualize such distribution by age.

Figure 38. *Placing variables in the bar-chart***.**



Click on "OK," and the output figure with your bar graph opens. Look at the output (Fig. 39). Now you can grasp how the factors distribute across age groups and can find the hidden patterns of values driving people's behaviors by age. In this case, for instance, you can see that the pattern of 'Xenophilia,' referring to respondents' positive attitude towards foods coming from other cultures, is particularly prominent in younger groups (18-25 through 34-41), while 'traditionalism' particularly distinguishes older respondents (75+ years). Repeat this analysis with other variables. Good work!

Figure 39. *Bar chart representing factors' distribution across respondents' age groups.*



Chapter 4

Cluster Analysis to identify consumer groups based on the hidden patterns found

4.1. The relevance of cluster analysis in the study of consumer culture and behaviour

The relevance of cluster analysis in the study of consumer culture and behavior lies in its ability to identify distinct groups or segments within a larger population based on shared characteristics, preferences, or behaviors. By grouping consumers with similar traits together, cluster analysis helps researchers and marketers gain a deeper understanding of the diversity within the consumer population. This segmentation allows for more targeted and effective strategies in areas such as marketing, product development, and customer engagement.

More generally, cluster analysis aids in identifying emerging ideal types of consumers and individuals in a shifting social context. This is critical in times of transition and great uncertainty when social trends become very unpredictable. Cluster analysis can reveal patterns, trends, and hidden relationships that may not be apparent when examining the overall consumer population as a whole. In essence, it is a valuable tool for tailoring approaches to different consumer segments and enhancing insights into the complexities of consumer culture and behavior.

4.2. What is Cluster Analysis?

Cluster analysis is a set of multivariate exploratory techniques of 'compression tools' (Reutterer and Dan, 2020) aimed at identifying homogeneous elements among the data and organizing these similarities into distinct groups. Pointing to identify which objects or subjects are similar, this method enables the segmentation and classification of a surveyed population (whatever its nature), proving crucial for target definition in whatever research context whose goal is classification. For this reason, cluster analysis is quite useful for researchers in all fields needing to make classifications of streams and watersheds, as well as psychiatric patients or types of companies on the market (Romesburg, 2004: 2). A cluster refers to a group of subjects (patients, consumers, etc.) or objects (products, brands, spatial areas, plants, etc.) with homogeneous characteristics, organized based on specific parameters of similarity within clusters and dissimilarity between clusters.

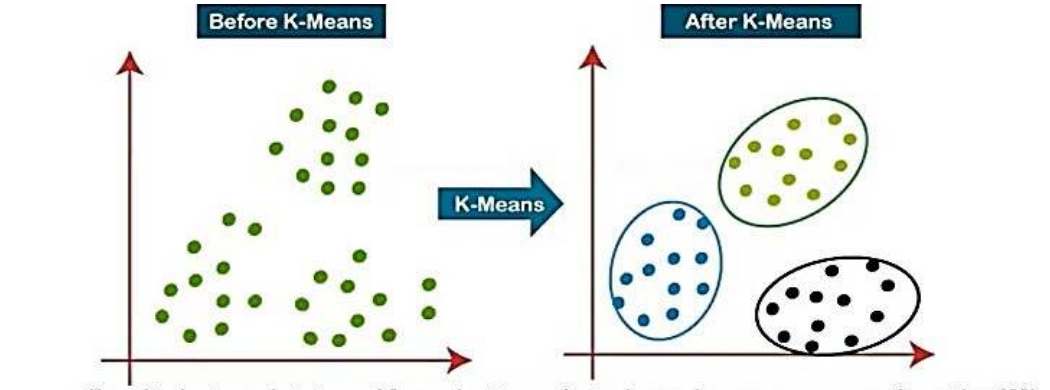
In social analysis, marketing, and analytics, the goal of using clusters is to represent types of consumers, particularly in marketing, where they serve as market segments. A proficient cluster analysis is a powerful tool in market research, as segmentation is essential for identifying specific customer segments that can be targeted in a customized marketing campaign, especially in a market where brands are increasingly aligning supply with demand.

Like any multivariate technique, Cluster Analysis is an exploratory approach that examines whether hidden correlations exist within a studied population based on similarities. This method identifies subgroups (segments) within a sample that are both internally homogeneous (with similar characteristics) and externally heterogeneous (showing dissimilarity between clusters). By combining qualitative and quantitative characteristics, cluster analysis enables predictions about groups based on their internal similarities and external dissimilarities.

Among clustering methods, non-overlapping distance-based techniques, where each observed entity belongs to a single group (as opposed to overlapping techniques where entities can belong to multiple groups simultaneously), are particularly useful, especially in the exploratory stage. Non-overlapping methods can be either hierarchical or nonhierarchical (Punj and Stewart, 1983). Nonhierarchical clustering, such as the *k*-means algorithm proposed in this study, is an exploratory partitioning technique. It begins with a predefined number (k) of clusters, and through an iterative process, it seeks to enhance the partition by minimizing the within-group dispersion, optimizing a 'minimum variance criterion' (Reutterer and Dan, 2020; Bock, 1974; Strasser, 2000).

The *k*-means algorithm, introduced by MacQueen (1967) and extended by various researchers (Jain and Dubes, 1988; Kaufman and Rousseeuw, 1990), is a popular distance-based clustering method. *K*-means partitions observations into a user-specified number of clusters and iteratively refines these clusters to achieve a specific numerical goal related to their distinctiveness. It is characterized by assigning objects to non-overlapping subsets (clusters) based on their distance from the centroid representing the central location of the cluster, that is the central tendency based on the average position of the data points within a cluster. This distance-based technique ensures that each object belongs to exactly one cluster and that each cluster is center-based and non-overlapping (Fig. 1).

Figure 1. *Ideal representation of a distance-based k-means (non-hierarchical) clustering technique.*


Before K-Means
After K-Means
K-Means
K-medie cluster analysis is used for explorative analysis when we have numerous cases (more than 100), when variables are both qualitative and quantitative, to identify the structure and segmentations of observed cases. It can be a starting step for further analysis.

A center-based cluster is a group of points where each point is closer to, or more similar to, the 'center' of the cluster than to the center of any other cluster. This is a result of the partition method, which minimizes within-group dispersion (Reutterer and Dan, 2020; Strasser, 2000). The centroid of a cluster represents the average position of all points within the cluster, serving as the most 'representative' point of the central tendency of that cluster and becoming its center.

K-means is recommended when dealing with a substantial number of cases (more than 100 valid respondents) and numerical/categorical ordinal variables. Particularly, as highlighted by Reutterer and Dan (2020: 25), partitioning methods like k-centroid clustering are often favored within marketing research in presence of quite extensive data, such as market basket data, when the goal is not only to identify sub-groups of population types, but to condense extensive datasets into a reduced number of representative points (centroids). Each centroid aims to accurately characterize a subset of the data while maintaining distinctiveness from other cluster centroids.

4.3. Preparation of the K-Means Cluster Analysis on SPSS

4.3.1. Identification of the variables to use in Cluster Analysis

As specified in Chapter 2, multivariate techniques, especially within the exploratory stages of research, are rarely used alone. They are often employed in tandem, an approach particularly fruitful in marketing and consumer research.

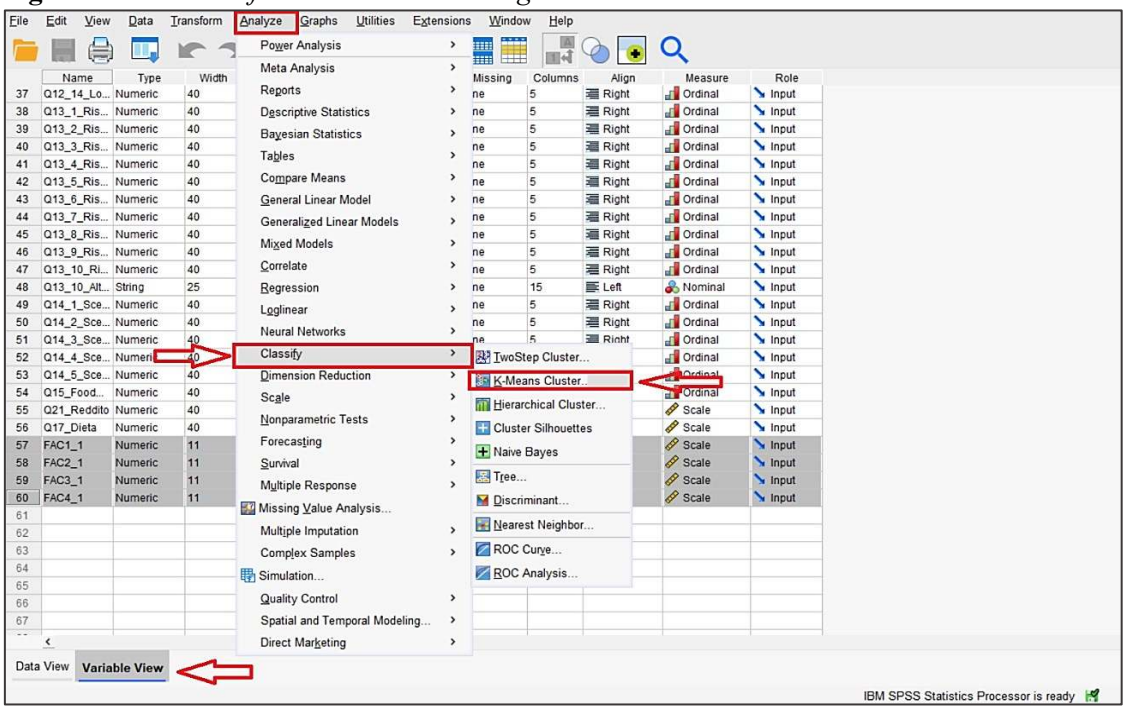
In this study, we propose to use Cluster Analysis as a subsequent step to Factor Analysis, shifting the focus from hidden patterns of relationships among underpinning values or drivers to hidden patterns of relationships among subjects (or objects) differently featured by those detected latent factors. Both techniques are employed in an exploratory perspective, with the common goal of bringing hidden relations to the forefront.

Using factors (or, in the case of parsimonious factor models, the variables constituting those factors) as discriminating variables to clusterize subjects implies that these underlying drivers or dimensions play a role in shaping subjects and guiding their positioning within a context, either closer to or farther from other subjects. Furthermore, since factors are already standardized variables, there is no need for additional standardization before utilizing them in cluster analysis. For more information on variable standardization, please refer to the last paragraph of this section. To initiate this analysis procedure, navigate to your dataset and open the 'Variable View' page ('Vista Variabile'). Choose the variables you intend to employ in your cluster analysis. As mentioned earlier, I recommend beginning with your extracted factors as the primary clustering variables.

Of course, Factors are variables that do not need to be standardized as they are already in that state.

Click on Analyze on the tool bar >> a menu opens. Click on ‘classify’ (Classifica) >> K-means Cluster (Cluster K-medie) (Fig. 2).

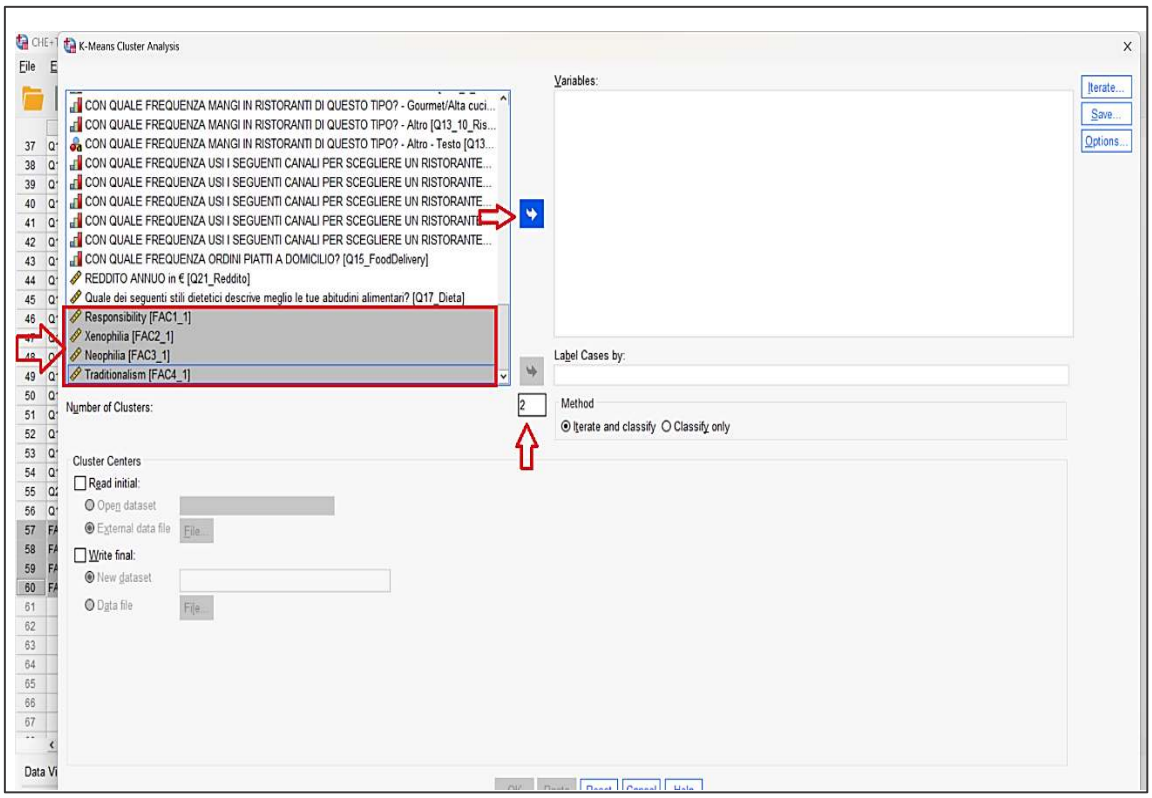
Figure 2. *Selection of the k-means clustering method*



4.3.2. Settings for implementing Cluster Analysis

After selecting the clustering method, a menu will appear, displaying all the variables in your dataset on the left window. Choose the variables you wish to include in your cluster analysis, in this case, your four factor variables located at the bottom of your dataset (Fig. 3). Move them to the 'variables' ('variabili') box on the right side by clicking the arrow.

Figure 3. *Selecting the clustering variables and setting the number of output clusters*


K-Means Cluster Analysis
File
CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Gourmet/Alta cuci...
CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Altro [Q13_10_Ris...
CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Altro - Testo [Q13...
CON QUALE FREQUENZA USI I SEGUENTI CANALI PER SCEGLIERE UN RISTORANTE...
CON QUALE FREQUENZA USI I SEGUENTI CANALI PER SCEGLIERE UN RISTORANTE...
CON QUALE FREQUENZA USI I SEGUENTI CANALI PER SCEGLIERE UN RISTORANTE...
CON QUALE FREQUENZA USI I SEGUENTI CANALI PER SCEGLIERE UN RISTORANTE...
CON QUALE FREQUENZA USI I SEGUENTI CANALI PER SCEGLIERE UN RISTORANTE...
CON QUALE FREQUENZA ORDINI PIATTI A DOMICILIO? [Q15_FoodDelivery]
REDDITO ANNUO in € [Q21_Reddito]
Quale dei seguenti stili dietetici descrive meglio le tue abitudini alimentari? [Q17_Dieta]
Responsibility [FAC1_1]
Xenophilia [FAC2_1]
Neophilia [FAC3_1]
Traditionalism [FAC4_1]
Variables:
Iterate...
Save...
Options...
Label Cases by:
Number of Clusters:
2
Method
Iterate and classify
Classify only
Cluster Centers
Read initial:
Open dataset
External data file
File...
Write final:
New dataset
Data file
File...

Default settings often suggest 2 output clusters. However, this may not be the most informative solution, especially when dealing with a large set of observed cases. Reducing the entire surveyed population to two large clusters might oversimplify the observed complexity. Since this is an exploratory analysis, it is recommended to start with at least 4 factors and, if needed, repeat the analysis with 3 factors. In some cases, with a very large surveyed population (around 100 subjects), you might even consider exploring 5 clusters. The optimal solution depends on the inferences and assumptions made by the researchers. Striking a good balance among internal cluster sizes is an initial criterion to determine the best solution.

After moving your selected variables to the right side, manually change the number of clusters from 2 to 4 as a first step (Fig. 4). Reminder: Recommended number of clusters to start with is 4, and then you may repeat with 3 if necessary.

Then click on ‘Iterate’ (itera)

A menu opens, where you’ll find default “10” number of iterations, meaning that the program expects convergence (optimal solution, i.e. the best number of factors) is reached within 10 iterations (Fig. 5).

Figure 4. *Inputting variables and manually changing the number of output clusters*

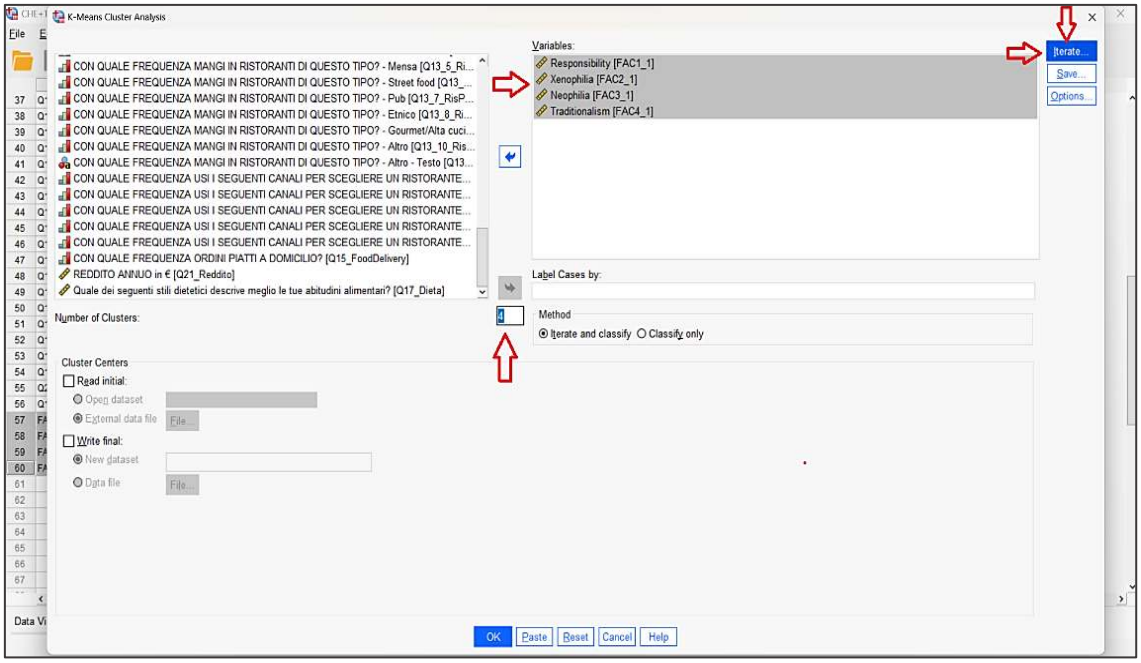
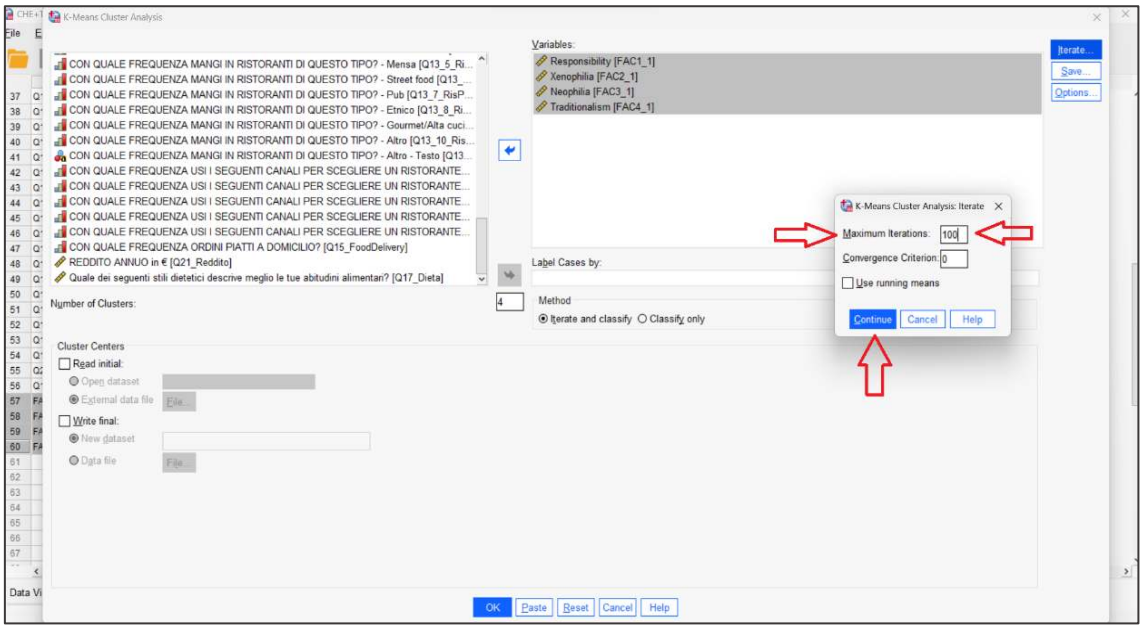


Figure 5. *Setting iterations*



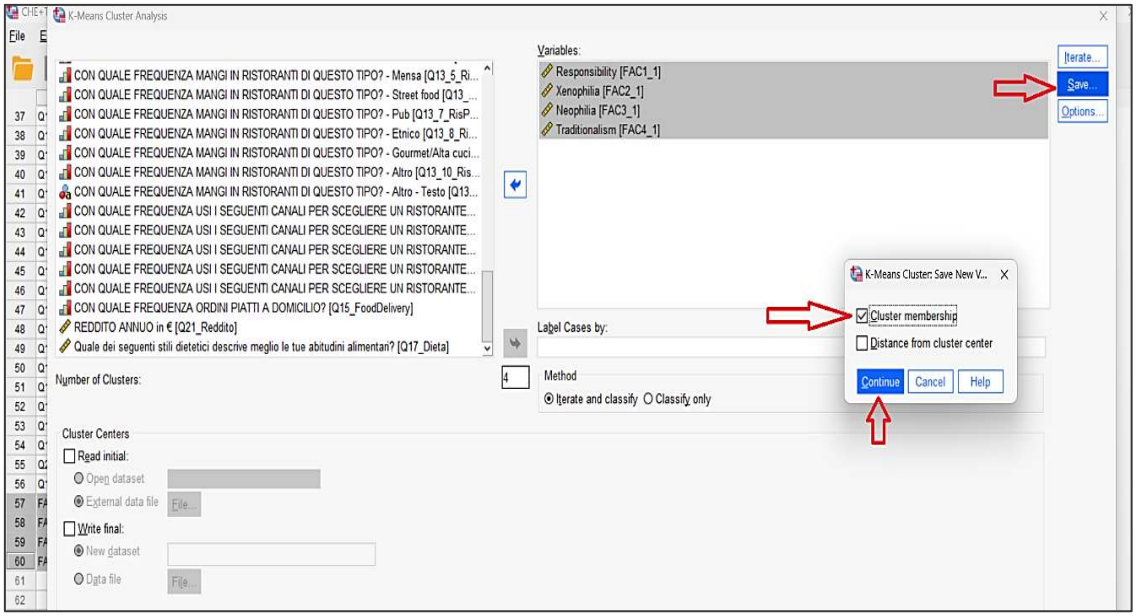
Like for Factor Analysis, also k-means Cluster Analysis is an iterative procedure, the partition is repeated again and again until convergence is reached. I recommend you to add one zero more to 10, because your cluster analysis might need more than 10 iterations to reach the convergence. 100 iterations is enough to have convergence reached.

Default criterium of convergence is 0, keep this parameter as it is.

Click on ‘Continue’

Click on Save. Another menu opens (Fig. 6); flag 'cluster membership' ('appartenenza cluster') to save the output cluster partition as variables. Once saved, you will find the cluster variable in your dataset at the bottom of the 'Variable View'.

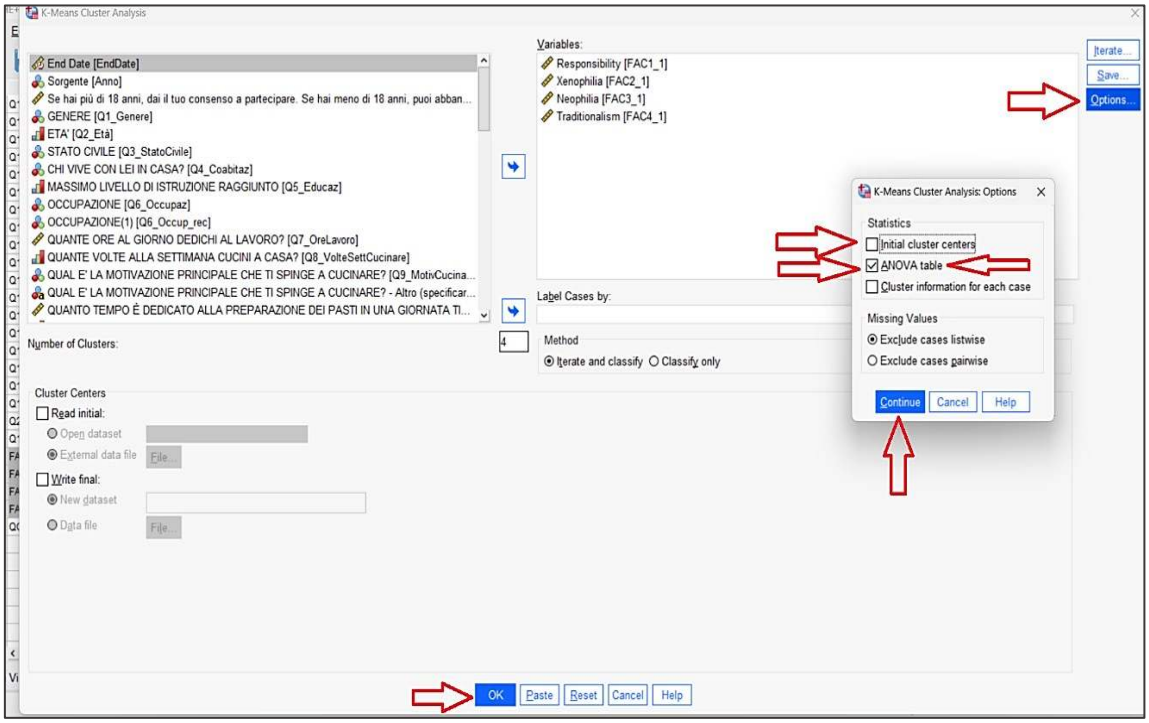
Figure 6. *Setting to save cluster membership as a variable*



Click on *Options*. A menu about 'Statistics' opens (Fig. 7). You will find the default flag for 'Initial cluster centres' ('centri iniziali dei cluster'). You can keep this setting as it is or unflag it. I suggest unflagging it to reduce redundancy in the output, as the information we need is the final cluster centres, and it will appear in any case.

Conversely, I recommend manually flagging 'ANOVA Table' ('Tabella ANOVA'). ANOVA will show you if (and which) selected variables are statistically significant in clustering (if "Sig." $p < 0.05$) and which of these variables are more discriminating (information provided by the 'Square mean' ('Media quadratica').

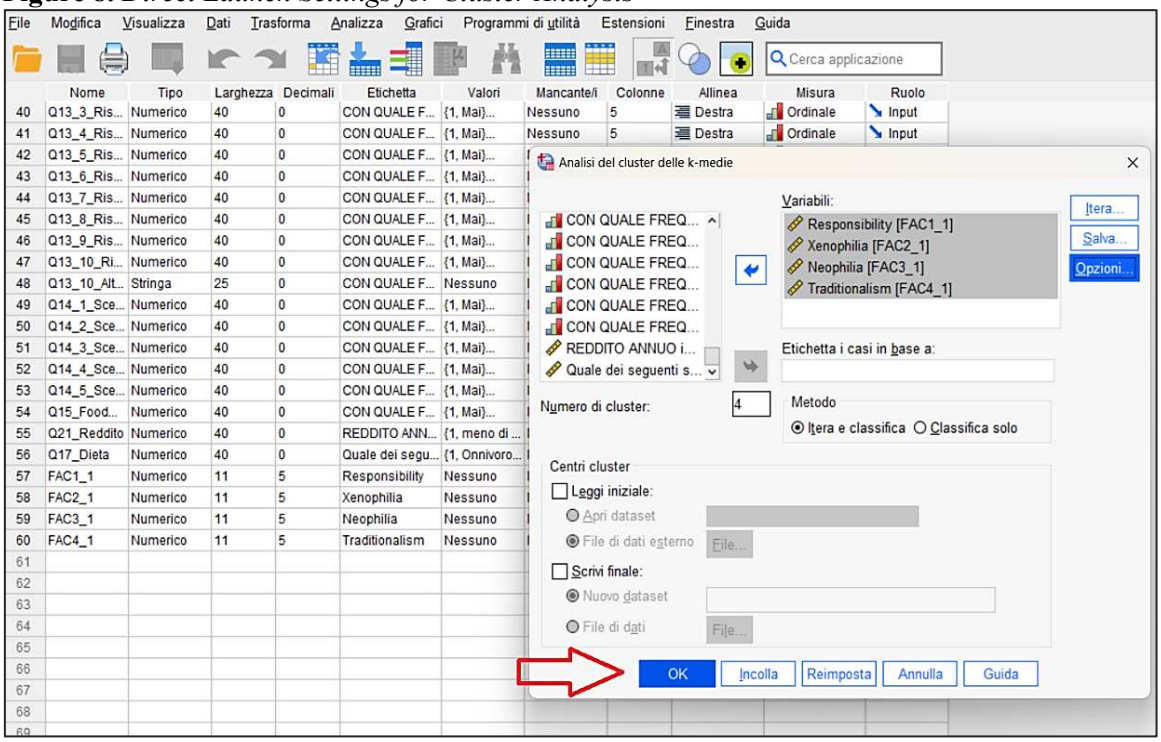
Figure 7. *Setting statistics about clustering*



After providing all these settings, click on 'OK' to launch your cluster analysis. Alternatively, you can click on 'paste' (incolla) instead of 'OK' to save your inputs in a syntax sheet. This second option allows you to track your steps and various attempts, making changes directly in your syntax strings without re-inputting settings in the next steps. Both methods are suitable for the analysis.

If you click on OK (Fig. 8), you will directly see your output and the variable you created in your dataset if you chose to save it as a variable (Fig. 10).

Figure 8. *Direct Launch Settings for Cluster Analysis*



If you click on 'paste', you'll create a syntax file, and you can view your cluster analysis settings saved, as shown in Fig. 9. To execute your syntax and generate the output, select the syntax and click on the green button in the toolbar.

Figure 9. *Settings of cluster analysis saved as a syntax*

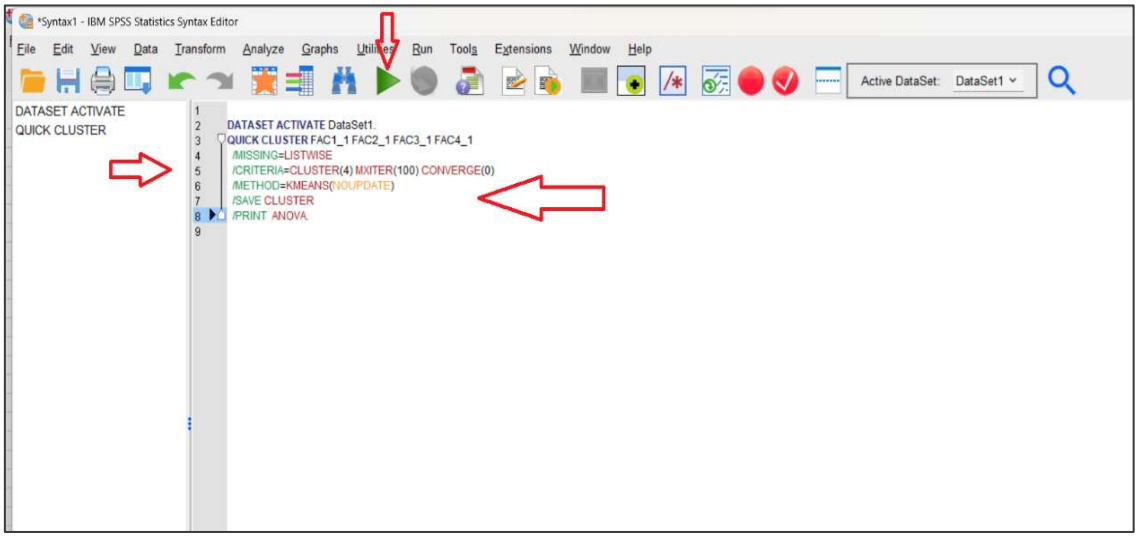
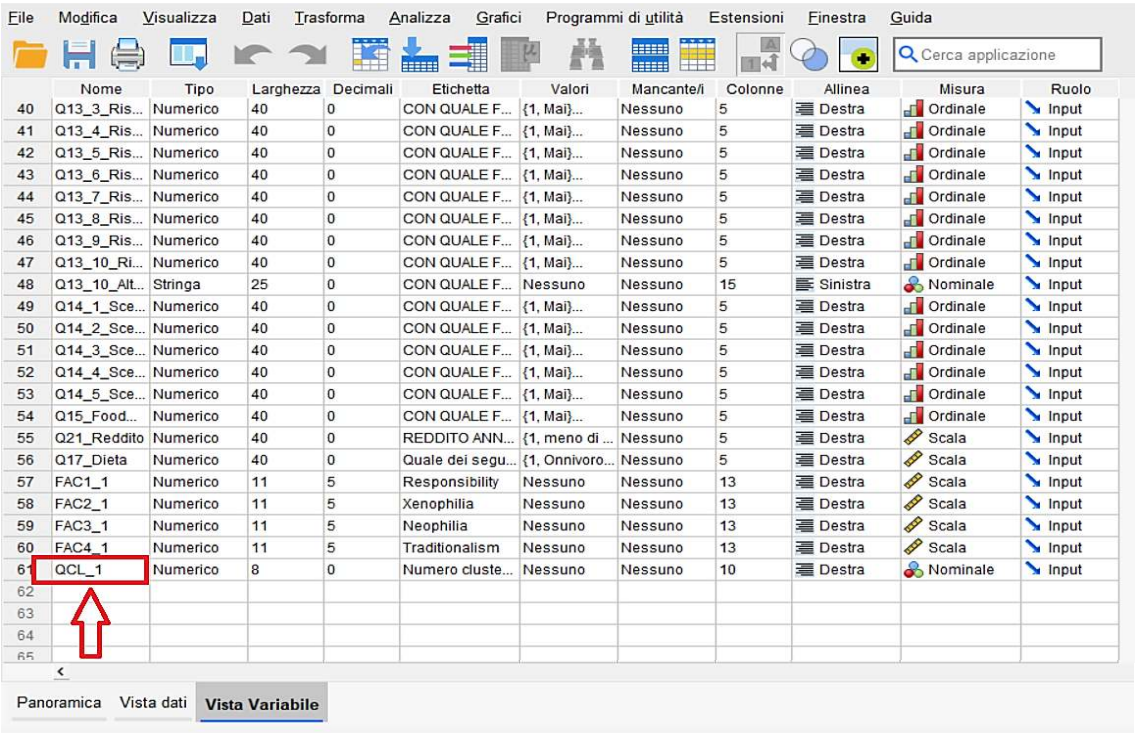


Figure 10. *Cluster variable created in your dataset.*

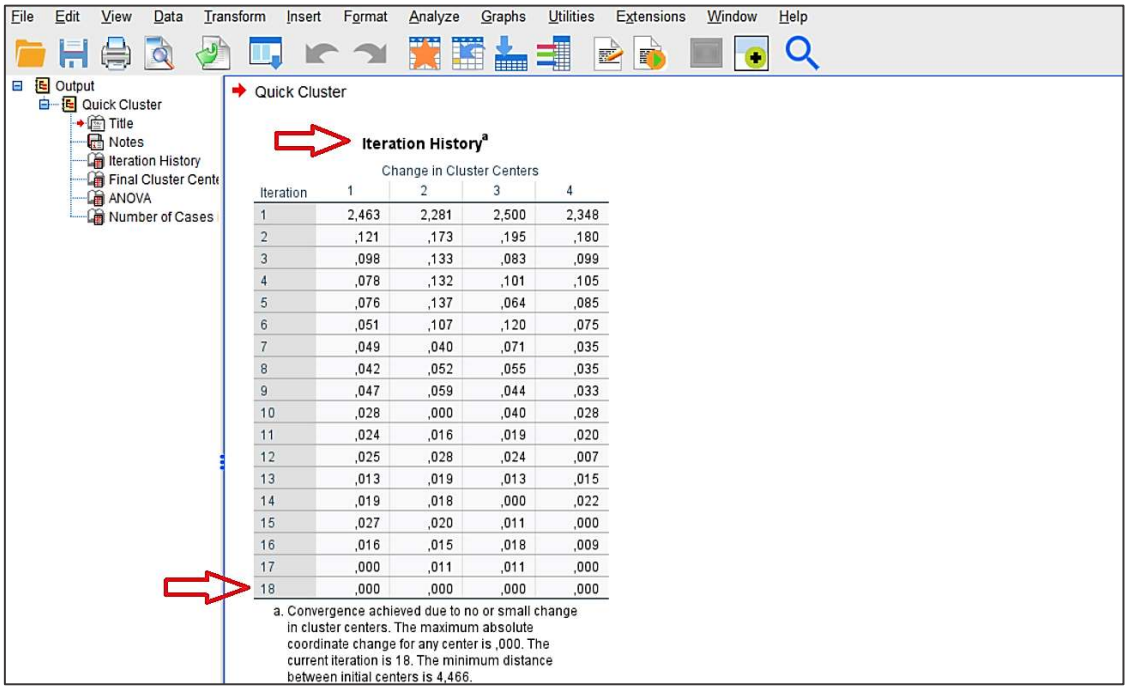

File Modifica Visualizza Dati Trasforma Analizza Grafici Programmi di utilità Estensioni Finestra Guida
Cerca applicazione
Panoramica Vista dati Vista Variabile

	Nome	Tipo	Larghezza	Decimali	Etichetta	Valori	Mancante/i	Colonne	Allinea	Misura	Ruolo
40	Q13_3_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
41	Q13_4_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
42	Q13_5_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
43	Q13_6_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
44	Q13_7_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
45	Q13_8_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
46	Q13_9_Ris...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
47	Q13_10_Ri...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
48	Q13_10_Alt...	Stringa	25	0	CON QUALE F...	Nessuno	Nessuno	15	Sinistra	Nominale	Input
49	Q14_1_Sce...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
50	Q14_2_Sce...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
51	Q14_3_Sce...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
52	Q14_4_Sce...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
53	Q14_5_Sce...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
54	Q15_Food...	Numerico	40	0	CON QUALE F...	{1, Mai}...	Nessuno	5	Destra	Ordinale	Input
55	Q21_Reddito	Numerico	40	0	REDDITO ANN...	{1, meno di ...	Nessuno	5	Destra	Scala	Input
56	Q17_Dieta	Numerico	40	0	Quale dei segu...	{1, Onnivoro...	Nessuno	5	Destra	Scala	Input
57	FAC1_1	Numerico	11	5	Responsibility	Nessuno	Nessuno	13	Destra	Scala	Input
58	FAC2_1	Numerico	11	5	Xenophilia	Nessuno	Nessuno	13	Destra	Scala	Input
59	FAC3_1	Numerico	11	5	Neophilia	Nessuno	Nessuno	13	Destra	Scala	Input
60	FAC4_1	Numerico	11	5	Traditionalism	Nessuno	Nessuno	13	Destra	Scala	Input
61	QCL_1	Numerico	8	0	Numero cluste...	Nessuno	Nessuno	10	Destra	Nominale	Input
62											
63											
64											
65											

4.4. Results and Interpretation of the Cluster Analysis

The initial information in the cluster analysis output concerns the number of iterations necessary for convergence (Fig. 11). In this instance, 18 iterations were conducted, affirming the earlier recommendation to adjust the default number of iterations (initially set at 10 and increased to 100) during the configuration stage.

Figure 11. *Iteration history to reach convergence*



Iteration	1	2	3	4
1	2,463	2,281	2,500	2,348
2	,121	,173	,195	,180
3	,098	,133	,083	,099
4	,078	,132	,101	,105
5	,076	,137	,064	,085
6	,051	,107	,120	,075
7	,049	,040	,071	,035
8	,042	,052	,055	,035
9	,047	,059	,044	,033
10	,028	,000	,040	,028
11	,024	,016	,019	,020
12	,025	,028	,024	,007
13	,013	,019	,013	,015
14	,019	,018	,000	,022
15	,027	,020	,011	,000
16	,016	,015	,018	,009
17	,000	,011	,011	,000
18	,000	,000	,000	,000

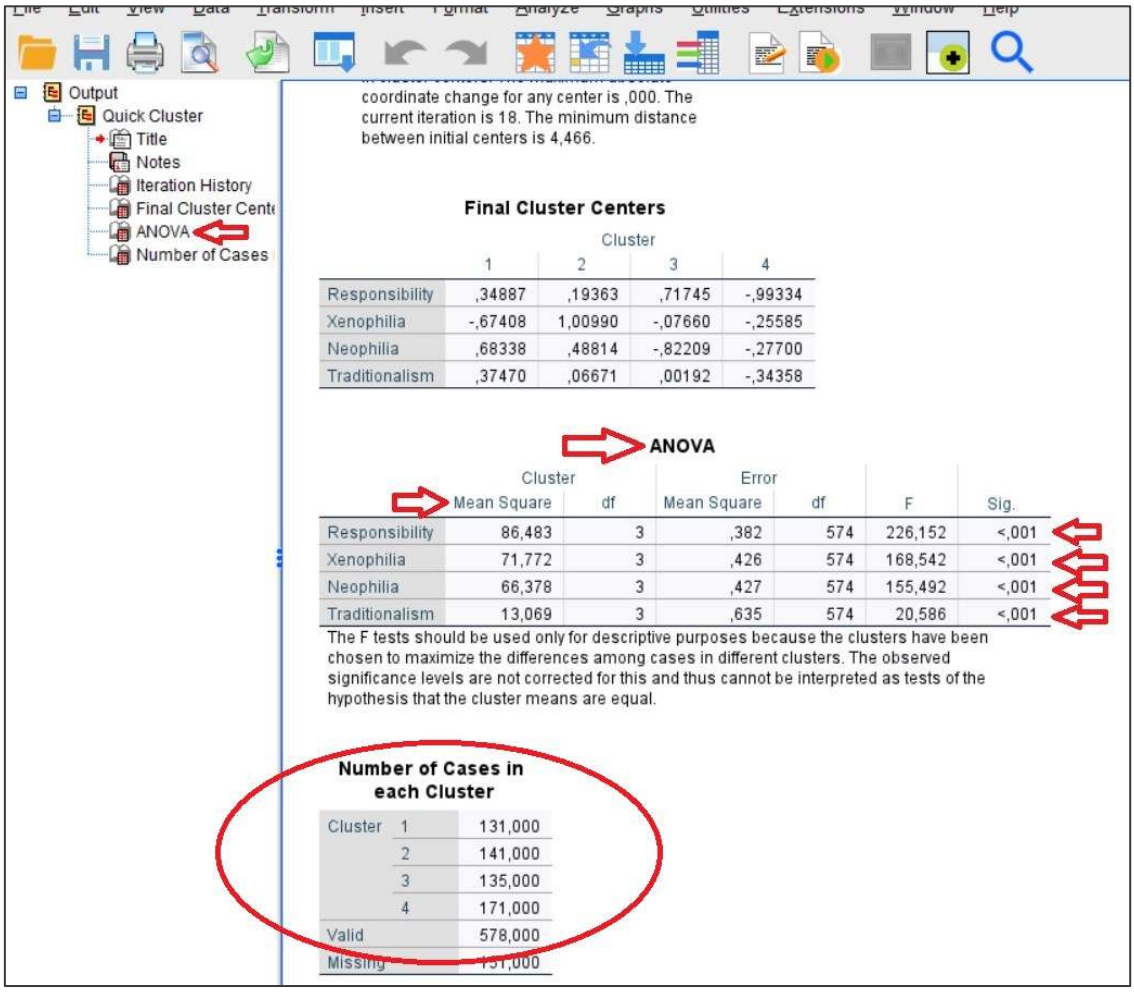
a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is ,000. The current iteration is 18. The minimum distance between initial centers is 4,466.

ANOVA Table (Fig. 12) represents the second crucial piece of information, complementing the distinctive characteristics of the clusters based on their distance from the center, considering k-means as a distance-based partitioning technique. The ANOVA Table offers insights into the statistical significance of each variable (in this context, factors) in differentiating groups, with significance indicated in the last column (Sig.<0.05 expected).

Additionally, the table provides information about the significance of each variable in discrimination, presented in the first column as 'Square mean' (media quadratica): a higher square mean indicates greater discriminatory power of that variable in defining the clusters.

Below the ANOVA table, information about the number of cases in each cluster and any missing values is presented. The internal numerosity of clusters is vital for evaluating balance. In this instance, the clusters exhibit good balance. However, if some clusters are highly unbalanced, such as having too many cases in one cluster and too few in another, it may indicate a suboptimal solution. Clusters with too few cases may potentially be outliers. While the number of cases within a cluster is not the sole determinant of the clustering quality, it serves as an indicative parameter. Disproportionate cluster sizes may warrant reconsideration of the chosen number of clusters in the analysis.

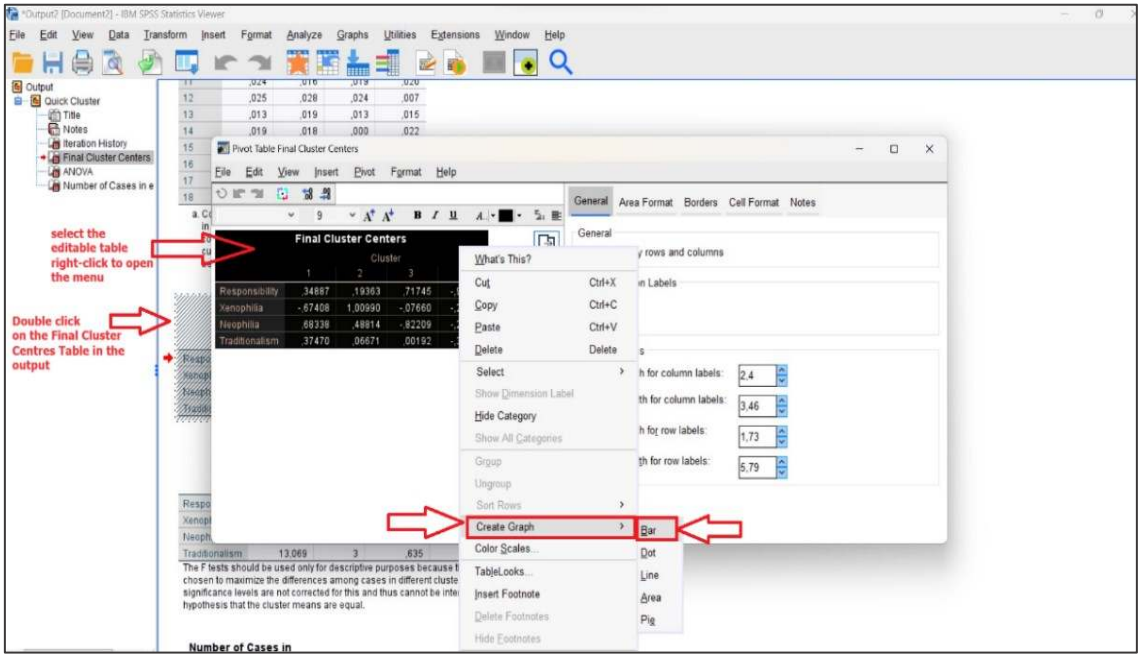
Figure 12. *Statistic information about clusters.*


Output
Quick Cluster
Title
Notes
Iteration History
Final Cluster Cente
ANOVA
Number of Cases
coordinate change for any center is ,000. The current iteration is 18. The minimum distance between initial centers is 4,466.
Final Cluster Centers
Cluster
1 2 3 4
Responsibility ,34887 ,19363 ,71745 -,99334
Xenophilia -,67408 1,00990 -,07660 -,25585
Neophilia ,68338 ,48814 -,82209 -,27700
Traditionalism ,37470 ,06671 ,00192 -,34358
ANOVA
Cluster
Error
Mean Square df Mean Square df F Sig.
Responsibility 86,483 3 ,382 574 226,152 <,001
Xenophilia 71,772 3 ,426 574 168,542 <,001
Neophilia 66,378 3 ,427 574 155,492 <,001
Traditionalism 13,069 3 ,635 574 20,586 <,001
The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.
Number of Cases in each Cluster
Cluster 1 131,000
2 141,000
3 135,000
4 171,000
Valid 578,000
Missing

In this case, ANOVA indicates that all four variables are statistically significant ($p < 0.05$). If some variables do not reach significance ($p > 0.05$), I recommend either rerunning the cluster analysis without those variables or excluding them from the graphical representation of the clusters.

The extracted clusters also exhibit a well-balanced distribution. To characterize our clusters and identify their prominent features based on how variables distinguish them, we can utilize the table of final cluster centers (Fig. 10). It's important to note that within the k-means methodology, final centers are considered the most representative information about clusters. For a more insightful understanding of the internal characteristics of each cluster, I recommend visualizing these center-cluster distances through a bar graph. To do so, double-click on the table of final cluster centers, open the editable version, select the entire table, right-click, and choose 'create graph' >> 'bar' (Fig. 13).

Figure 13. *Create a bar graph to visualize the clusters*

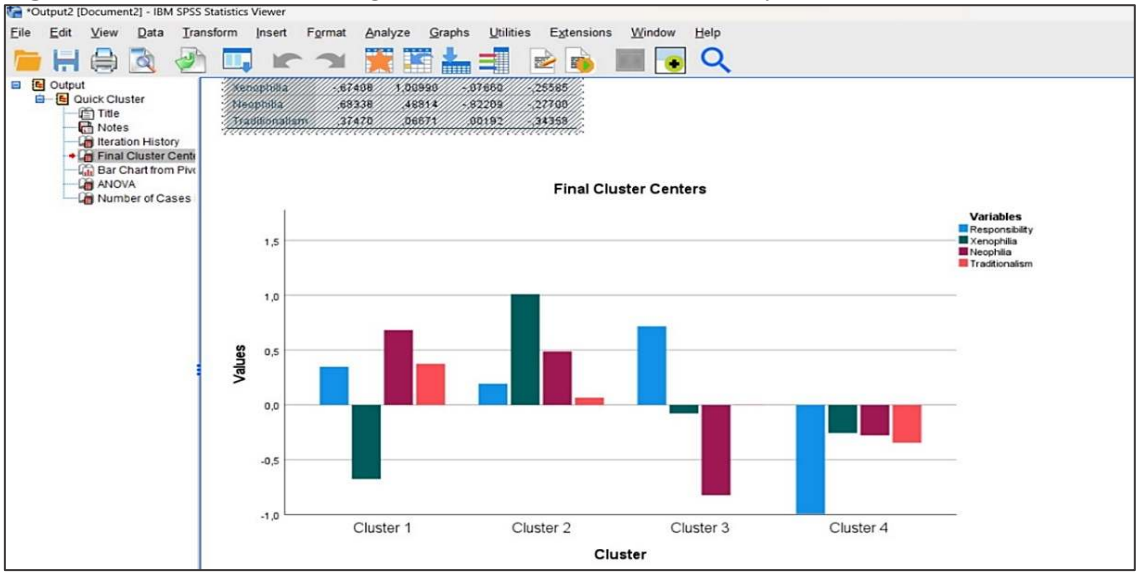

select the editable table right-click to open the menu
Double click on the final Cluster Centres Table in the output
Final Cluster Centers
Create Graph
Bar

A bar chart appears in the output, illustrating the distribution of the selected variables (in this case, the extracted factors) within the clusters, uniquely featuring each cluster (Fig. 14).

Such graphical visualization is crucial for labeling clusters with descriptive names.

The names should be assigned based on the trend and direction of the bars that most distinctly deviate from the center (0). For instance, in this graph, ***Cluster 1*** is primarily characterized by negative values of 'Xenophilia,' positive values of 'Neophilia,' but also with a moderate interest in 'tradition' and 'responsible consumption,' outlining a profile of **'non-conservative gastronationalist consumers.'** ***Cluster 2*** is mainly featured by 'Xenophilia' and 'Neophilia,' outlining a profile of an **'adventurous consumer.'** ***Cluster 3*** is primarily featured by 'Responsibility' with quite negative scores of 'Neophilia,' outlining a profile of a **'Responsible minimalist consumer.'** ***Cluster 4*** is characterized by negative values across all variables, with a distinct incidence of the absence of responsibility, outlining a profile of an **'unresponsible indifferent consumer.'**

Figure 14. *Bar chart visualizing clusters based on their distance from the centers*



To name the cluster and see them with their names in the graph, move to the dataset, variable view, at the bottom of your dataset, you'll find the cluster variable at the very end.

Click on the right angle (with three dots) of corresponding box in the column of 'values' (etichette). The label menu opens (Fig. 15). Click on the symbol + and insert the number 1 under 'value' and write down the name of the cluster number 1 ('non-conservative gastronationalist consumer') under 'label'. Then repeat the operation for labelling cluster 2: click again on the symbol + insert number 2 under 'value' and write down the name of the cluster number 2 ('adventurous consumer') under 'label'. Repeat this procedure for all four clusters, and then click on 'ok'.

Now you will find your cluster variable with its categories labeled with names, each identifying a cluster.

Figure 15. *Labelling clusters with a name*

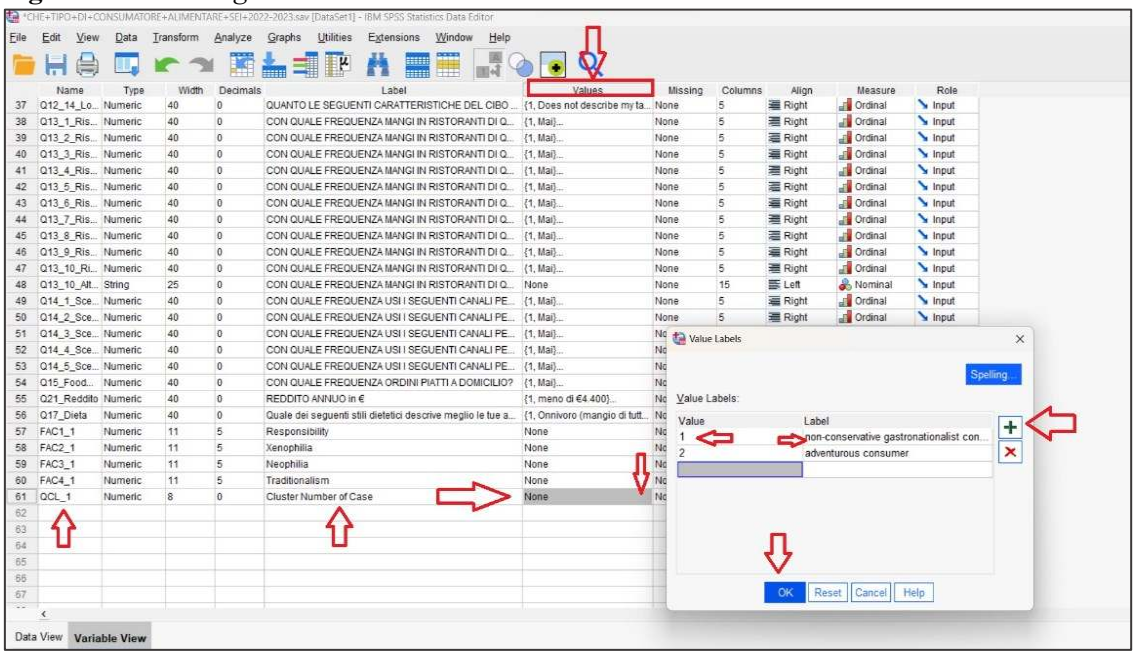
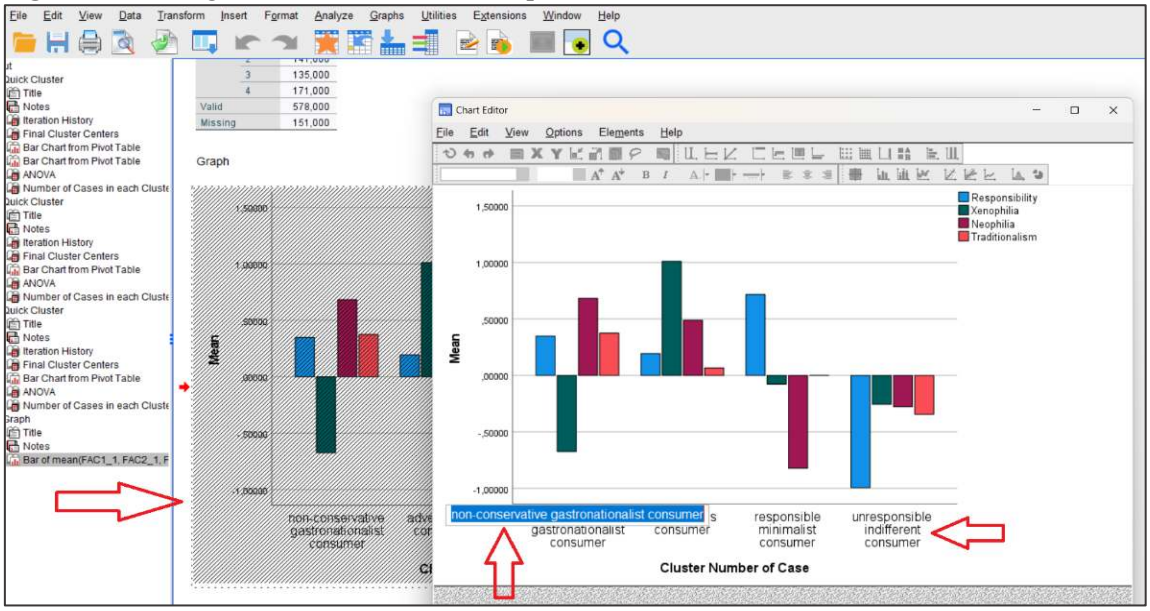


Figure 16. *Adding Cluster Names to the Graph*.

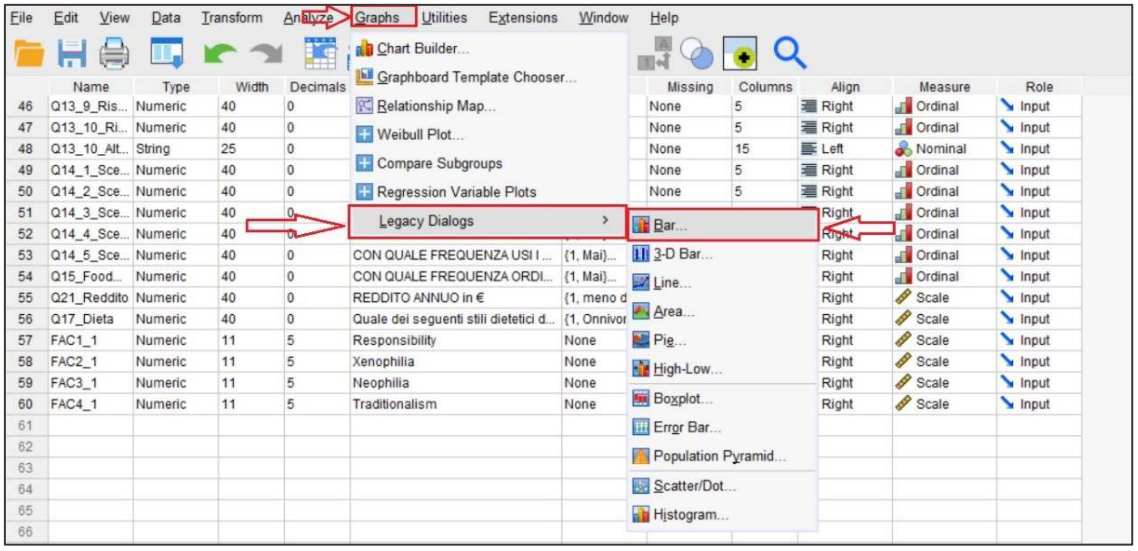


After saving the labels, I recommend manually entering the names of the clusters in the bar graph. Double-click on the graph to open an editable version, then click on the boxes corresponding to clusters 1, 2, 3, and 4. Overwrite their names as shown in Fig. 16.

4.5. Representing Cluster Distribution Across Sociodemographic and Personal Lifestyle Characteristics

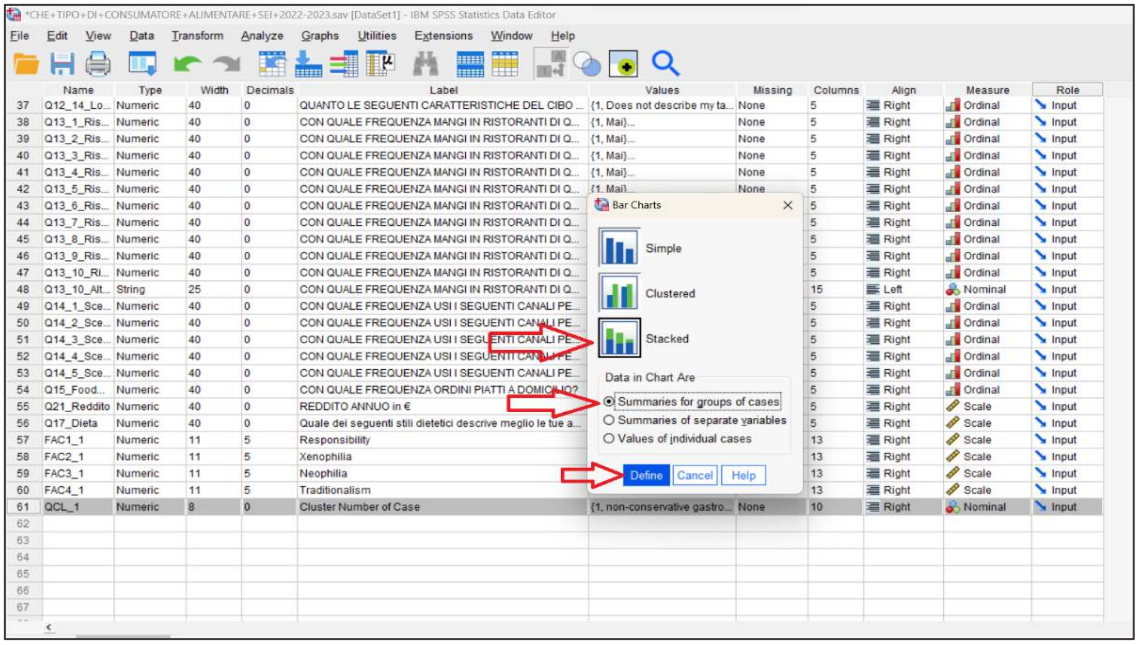
If we want to examine the characteristics of computed clusters in terms of personal traits like gender, age, dietary styles, etc., using graphs, particularly bar charts, is advisable. Of course, it is always recommended to check for statistical significance (Sig. <0.05) between clusters and the socio-demographic or personal variable we intend to analyze. To do that, move to variable view, then click on 'Graphs' on the toolbar and a menu opens. Like for Factor Analysis, select barcharts (Fig. 17).

Figure 17. *Settings for visualizing clusters' distribution across personal characteristics*



A menu opens, in this case the best graphic solution is 'stacked' ('in pila') bar charts, setting that data in the bar chart are summaries for groups of cases ('riepiloghi per gruppi di casi') (Fig. 18).

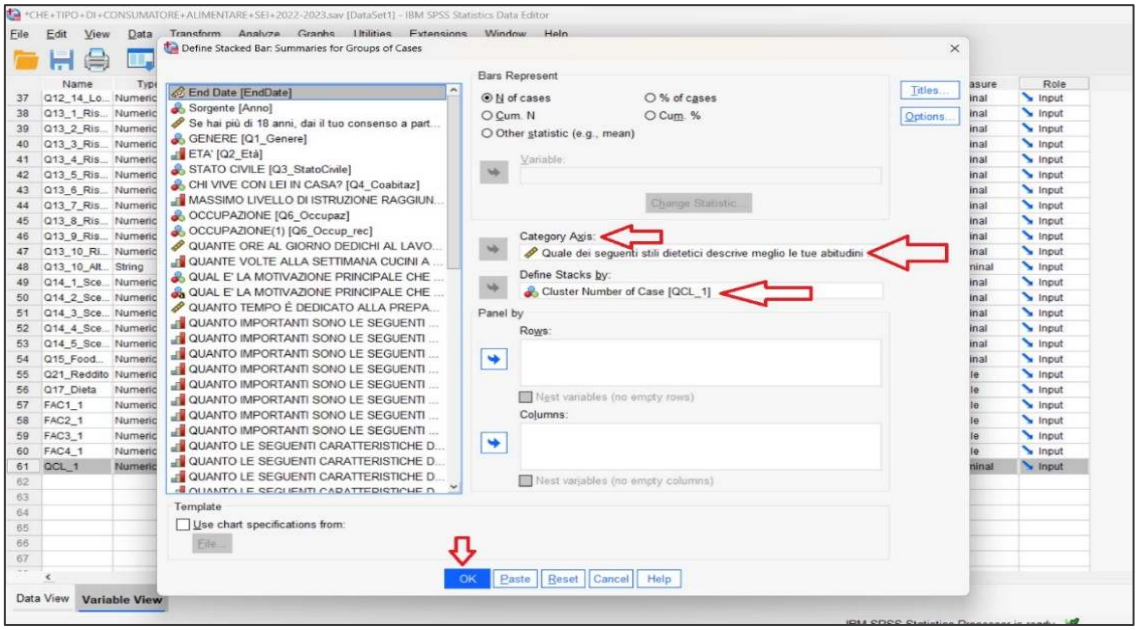
Figure 18. *Settings for stacked bar charts to visualize clusters*



Click on 'Define.' Another menu will open, similar to Fig. 19. In the box 'Category Axis' ('asse delle categorie'), move the input variable of the personal characteristic you want to cross with the clusters. In this case, for instance, 'dietary style' (the horizontal axis represents this variable).

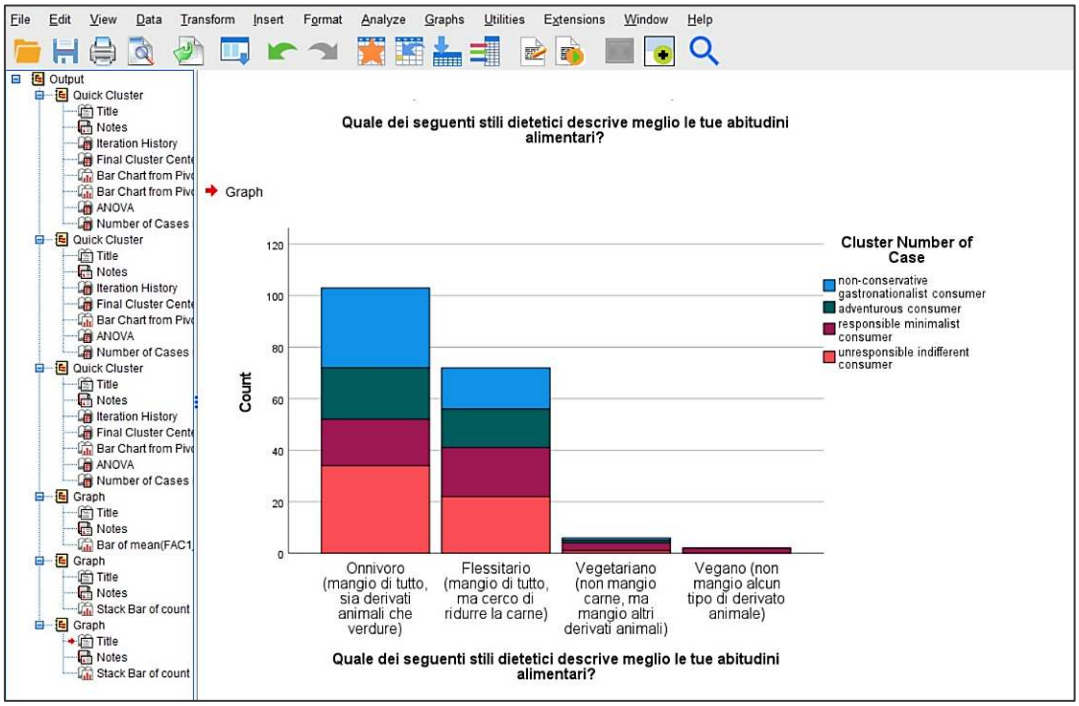
In the box 'Define stacks by' ('definisci pile tramite'), move your cluster variable (this means that the stacks represent the clusters).

Figure 19. *Settings to Define Stacks by clusters*



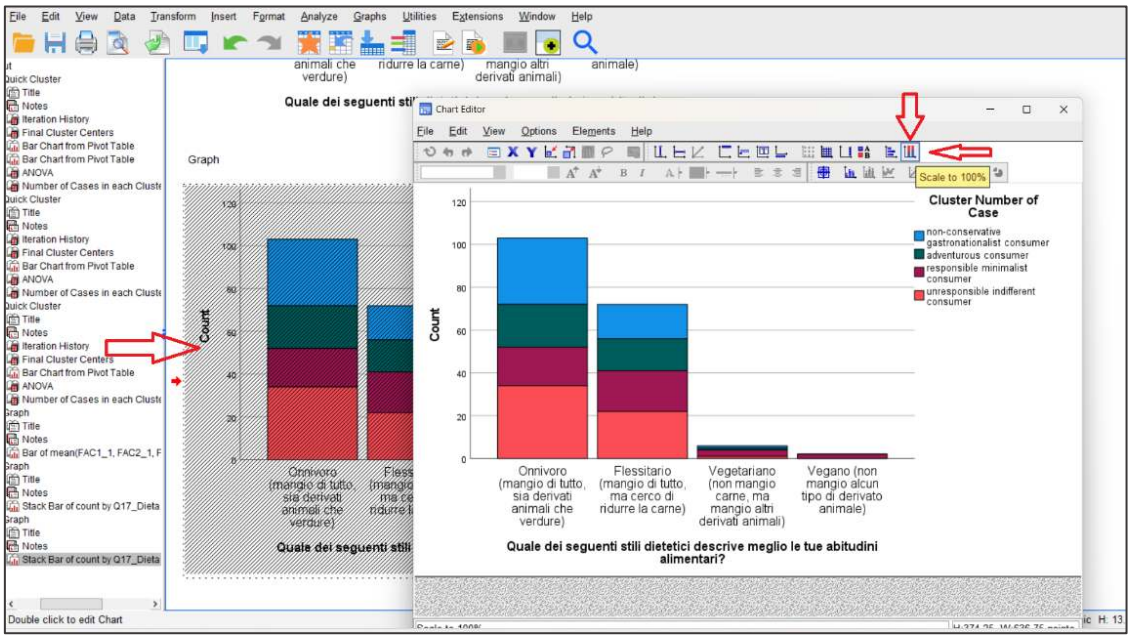
The diagram illustrates the predominant dietary style group for each of the four clusters. The size of each cluster is taken into account in the representation, revealing that in our sample, the majority of respondents identify as omnivores and flexitarians, while vegetarians and vegans constitute a minority (Fig. 20).

Figure 20. *Stacked Bar Graph Representing Cluster Distribution by Dietary Styles.*



To better capture the distribution of clusters across dietary styles, it is recommended to standardize the bars by 100, displaying the results in percentages rather than absolute cases. To standardize the bars by 100: Double-click on the graph, and the graph editor will open. Then, click once on the icon with the bars in the upper-right toolbar (Fig. 21).

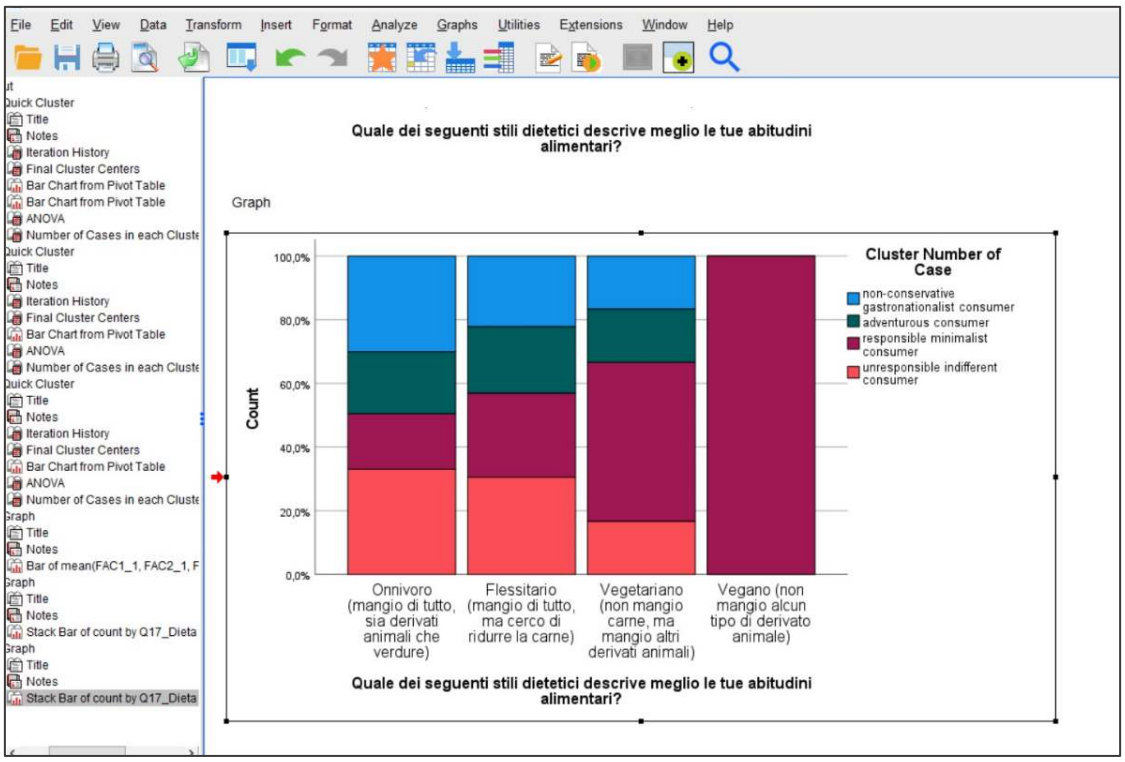
Figure 21. *Settings for scaling by 100 the Bar Chart.*


File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help
Chart Editor
File Edit View Options Elements Help
Scale to 100%
Graph
Count
Cluster Number of Case
non-conservative gastronationalist consumer
adventurous consumer
responsible minimalist consumer
unresponsible indifferent consumer
Onnivoro (mangio di tutto, sia derivati animali che verdure)
Flessitario (mangio di tutto, ma cerco di ridurre la carne)
Vegetariano (non mangio carne, ma mangio altri derivati animali)
Vegano (non mangio alcun tipo di derivato animale)
Quale dei seguenti stili dietetici descrive meglio le tue abitudini alimentari?
Double click to edit Chart

You will at the end obtain a scale graph like the one represented in Fig. 20, where you can clearly see how the cluster distribute across dietary style groups. You can see, for instance, that vegans are wholly present in the cluster of responsible minimalist consumers, soon followed by Vegetarians.

While omnivores crowd both the cluster of unresponsible indifferent consumers and the one of non-conservative gastronationalist consumers.

Figure 22. *Stacked Bar Chart scaled by 100*


File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help
Quale dei seguenti stili dietetici descrive meglio le tue abitudini alimentari?
Graph
Cluster Number of Case
non-conservative gastronationalist consumer
adventurous consumer
responsible minimalist consumer
unresponsible indifferent consumer
Count
100,0%
80,0%
60,0%
40,0%
20,0%
0,0%
Onnivoro (mangio di tutto, sia derivati animali che verdure)
Flessitario (mangio di tutto, ma cerco di ridurre la carne)
Vegetariano (non mangio carne, ma mangio altri derivati animali)
Vegano (non mangio alcun tipo di derivato animale)
Quale dei seguenti stili dietetici descrive meglio le tue abitudini alimentari?

4.6. Standardizing Variables for Factor Analysis

Usually, in consumer analysis, particularly in marketing, the variables employed for clustering the observed cases include items related to

These variables are initially eminently qualitative but they are typically presented in surveys as ordinal scales to enable treatment as quantitative items, measuring aspects that are inherently challenging to quantify. Even though scales may be designed with the same number of points, they might measure frequency, level of agreement, or importance attached to something. A general challenge arises in dealing with variables like these, that measure different magnitudes, potentially arbitrarily affecting the similarities among objects. Keep in mind that Cluster Analysis is a multivariate classification technique that relies on numerical taxonomy to identify similarities among objects *as if they were dimensionless*.

So, the first precaution when applying cluster analysis to consumer research is to use the same type of variables for clustering objects (which, in most cases, are subjects) to mitigate these biases. This involves using all ordinal scales with the same interval and avoiding, as much as possible, nominal multiple-choice variables.

However, this alone is not sufficient to eliminate arbitrariness in treating different dimensions as if they were the same. To achieve this goal, the standardization of variables in the matrix table is strongly recommended. The reasons for standardization are clearly expressed in Romesburg's pivotal book, *Cluster Analysis for Researchers*:

> There are two main reasons for standardizing a data matrix. First, the units you choose for measuring attributes can arbitrarily affect the similarities among objects. By standardizing the attributes and recasting them in dimensionless units, you remove the arbitrary affects. Second, standardizing makes attributes contribute more equally to the similarities among objects. For example, if the range of values on the first attribute is much greater than the range of values on the second, then the first attribute will carry more weight in determining the similarities among objects. When this is undesirable in the context of your research goal, you can compensate for the effect by standardization (Romesburg, 2004: 78).

Standardization is a preliminary operation that should be performed soon after choosing the variables for Cluster Analysis. In the case presented in the previous pages, we used the factors extracted through the preceding Factor Analysis, which are already standardized variables. However, let's imagine a scenario where we use not the factors but the eleven variables correlated to the factor structure. This situation is illustrated in Fig. 23, where, although all scales are 5-point, some variables represent scales of importance (e.g., 1. Not at all important, 2. Slightly important, etc.), while others are scales of opinion (e.g., 1. Does not describe my taste, 2. Describes my taste slightly well, etc.).

Figure 23. *Scale Variables for Cluster Analysis measuring different Dimensions*

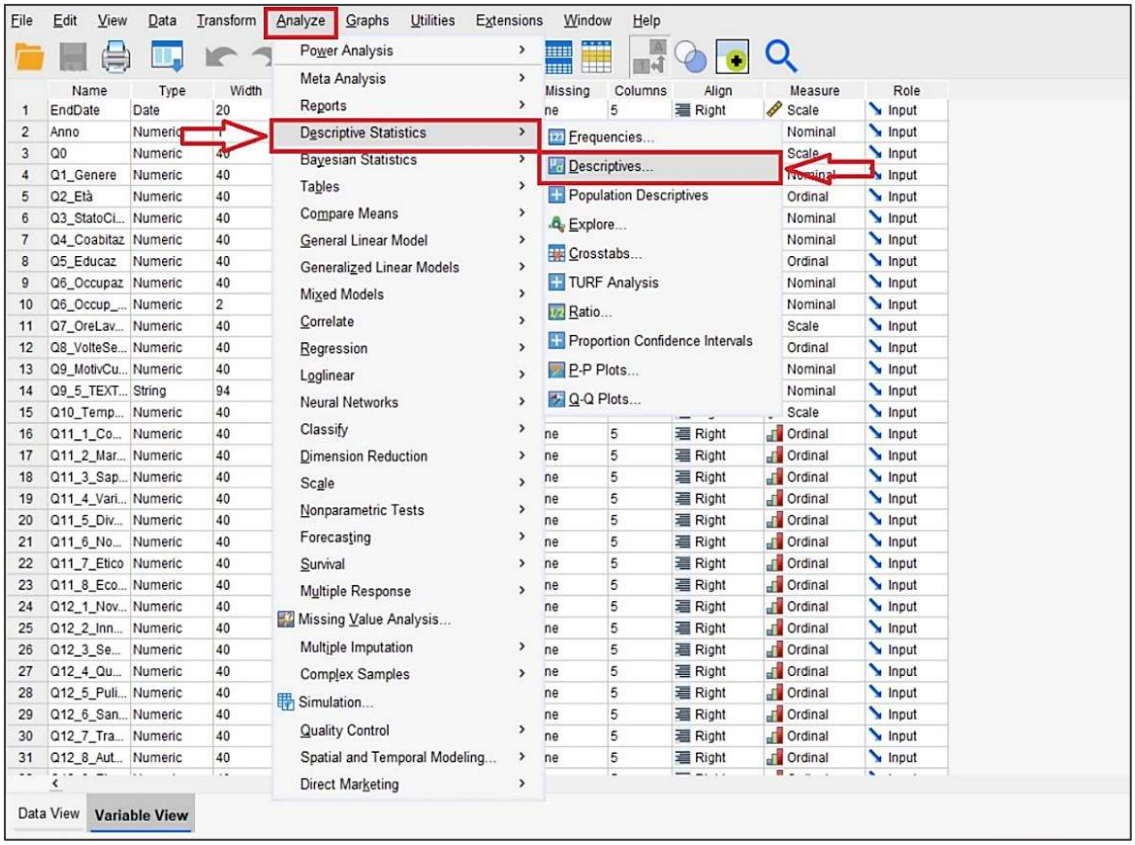
	Name	Type	Width	Decimals	Label	Values
13	Q9_MotivCu...	Numeric	40	0	QUAL E' LA MOTIVAZIONE PRINCIPALE CHE TI SPINGE A CUCINARE?	{1, Necessità}...
14	Q9_5_TEXT...	String	94	0	QUAL E' LA MOTIVAZIONE PRINCIPALE CHE TI SPINGE A CUCINARE? - Altro (specificare) - Testo	None
15	Q10_Temp...	Numeric	40	0	QUANTO TEMPO È DEDICATO ALLA PREPARAZIONE DEI PASTI IN UNA GIORNATA TIPICA IN CASA TUA?	{1, Less than 30 mins}...
16	Q11_1_Co...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Confortevole (quando sono giù, nervoso, o mentre...	{1, Not at all important}...
17	Q11_2_Mar...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Marca affidabile	{1, Not at all important}...
18	Q11_3_Sap...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Saporito	{1, Not at all important}...
19	Q11_4_Vari...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Disponibile in vari gusti	{1, Not at all important}...
20	Q11_5_Div...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Di una cultura diversa	{1, Not at all important}...
21	Q11_6_No...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Alternativo, non convenzionale	{1, Not at all important}...
22	Q11_7_Etico	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Etico	{1, Not at all important}...
23	Q11_8_Eco...	Numeric	40	0	QUANTO IMPORTANTI SONO LE SEGUENTI CARATTERISTICHE NEL TUO CIBO PREFERITO? - Ecologico	{1, Not at all important}...
24	Q12_1_Nov...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Novità nella tradizione culinaria	{1, Does not describe my taste}...
25	Q12_2_Inn...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto con tecniche innovative	{1, Does not describe my taste}...
26	Q12_3_Se...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Semplice e veloce da preparare	{1, Does not describe my taste}...
27	Q12_4_Qu...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Buon rapporto qualità-prezzo	{1, Does not describe my taste}...
28	Q12_5_Puli...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Pulito e sicuro	{1, Does not describe my taste}...
29	Q12_6_San...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Sano o conforme a una dieta	{1, Does not describe my taste}...
30	Q12_7_Tra...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Tradizionale	{1, Does not describe my taste}...
31	Q12_8_Aut...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Autentico	{1, Does not describe my taste}...
32	Q12_9_Ela...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Elaborato con lunga preparazione	{1, Does not describe my taste}...
33	Q12_10_Et...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - "Etnico" o di altre culture	{1, Does not describe my taste}...
34	Q12_11_C...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Costoso o raro	{1, Does not describe my taste}...
35	Q12_12_C...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Gustoso e confortevole	{1, Does not describe my taste}...
36	Q12_13_Eco	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Ecologico	{1, Does not describe my taste}...
37	Q12_14_Lo...	Numeric	40	0	QUANTO LE SEGUENTI CARATTERISTICHE DEL CIBO DESCRIVONO IL TUO GUSTO? - Prodotto localmente	{1, Does not describe my taste}...
38	Q13_1_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Fast food	{1, Mai}...
39	Q13_2_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - All you can eat	{1, Mai}...
40	Q13_3_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Pizzeria/Trattoria	{1, Mai}...
41	Q13_4_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Bar/Brasserie	{1, Mai}...
42	Q13_5_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Mensa	{1, Mai}...
43	Q13_6_Ris...	Numeric	40	0	CON QUALE FREQUENZA MANGI IN RISTORANTI DI QUESTO TIPO? - Street food	{1, Mai}...

Data View | Variable View

Standardization is essential for the reasons mentioned earlier, and it becomes even more crucial when the cluster involves variables with different intervals—ranging from 5-point scales to 3-point scales and binary variables such as YES/NO.

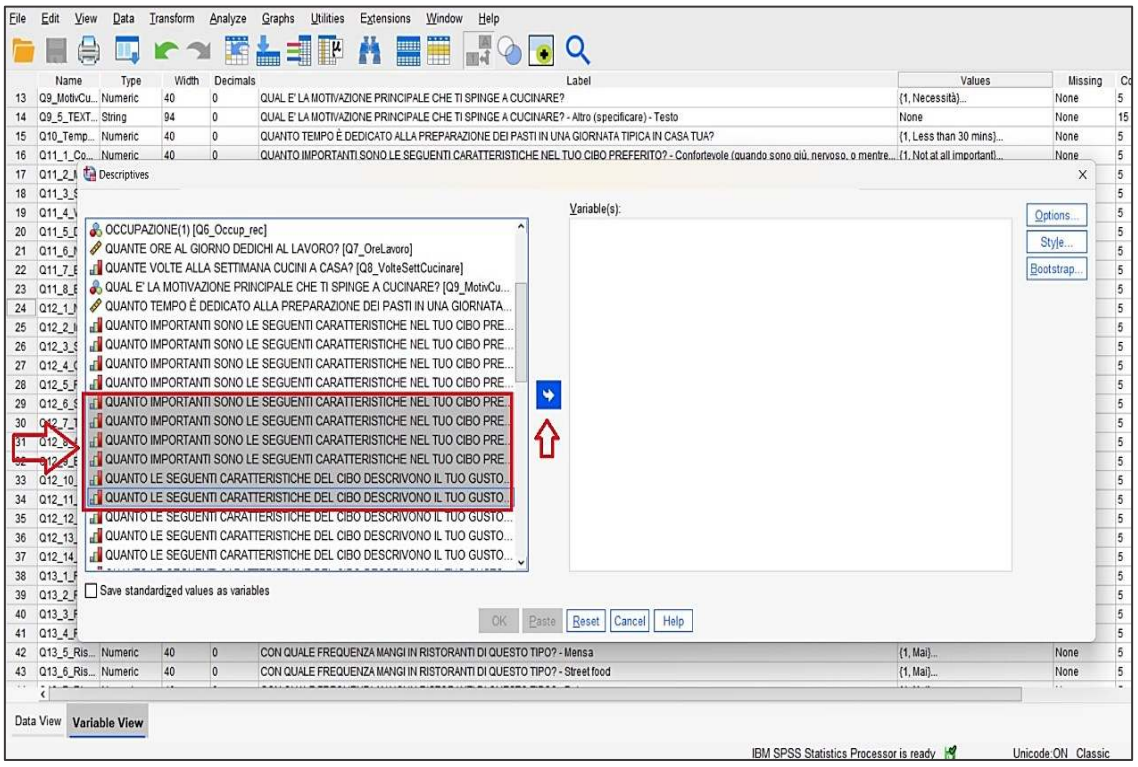
To standardize variables in SPSS, navigate to the toolbar, click on 'Analyze,' and then select 'Descriptive Statistics' (*statistiche descrittive*) and then again 'Descriptives' (descrittive) (Fig. 24).

Figure 24. *Settings to standardize Variables for Cluster Analysis*



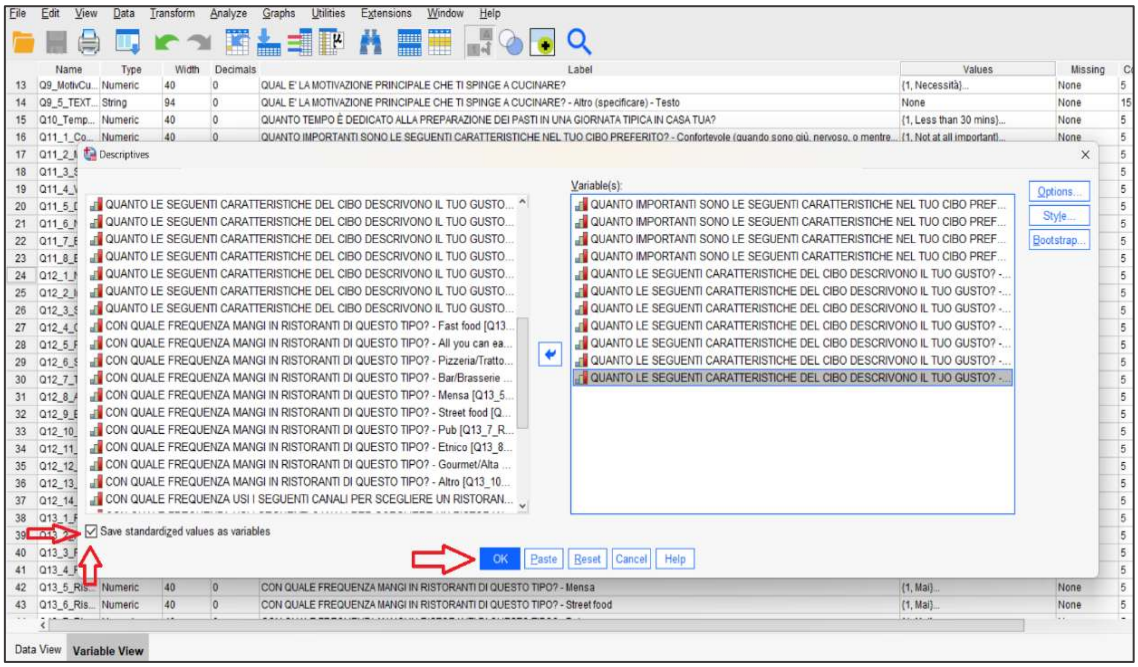
A menu will open. Select the variables you want to standardize and move them from the left to the right box 'Variable(s)' (*variabili*), as shown in Fig. 25.

Figure 25. *Selecting Variables to standardize*



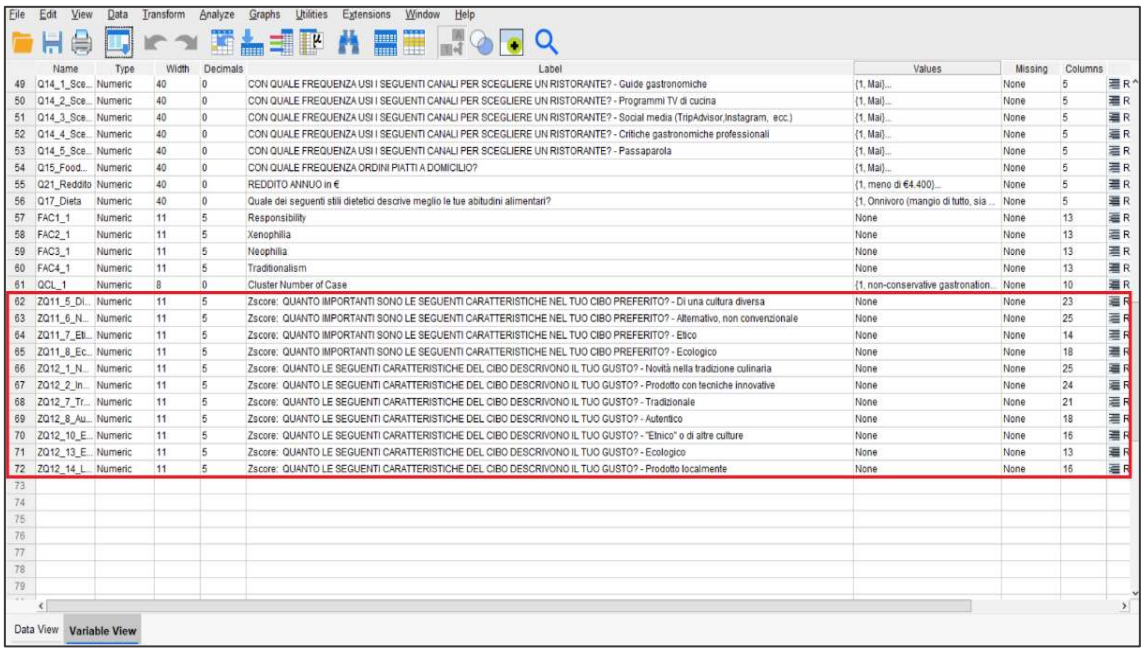
Flag the box bottom-left 'Save standardized values as variables' (*salva valori standardizzati come variabili)* and then click 'OK' (Fig. 26).

Figure 26. *Save Standardized Variables*



At the bottom of your database in the 'Variable View' page, you will find your standardized variables saved as 'Zscore variables'. Use these 'Z variables', not the original ones, in your k-means cluster analysis (Fig. 25). And remember, while standardization is recommended in Cluster Analysis, it becomes necessary when dealing with specific scenarios involving variables of different types or varying scales.

Figure 25. *Standardized Variables in the dataset ready for Cluster Analysis*



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During times of profound social change, such as the present, when predictive capabilities waver and perspectives narrow, understanding consumer desires and motivations becomes crucial for navigating uncertainty and aligning supply with demand. This book provides practical guidance for explanatory social research in consumer analysis, offering selected multivariate techniques that blend rational quantification with the reflective aim of capturing the complex web of underlying dimensions, value-based motivations and factors influencing consumer behaviors. Unlike a traditional methodology manual, this essential handbook shows the practical application of these techniques, translating the ungraspable inner dimensions driving behaviors into the observational, measurable, and generalizable language of variables.

Maria Giovanna Onorati is a Sociologist of Cultural and Communicative Processes at the University of Gastronomic Sciences in Pollenzo (Italy), where she teaches Sociology of Consumer Culture, Social Inclusion, and Multivariate Analysis Techniques for Consumer Analysis. Her research centers on food consumer dynamics, exploring food's role in cultural identification, social differentiation, and potential contributions to social inclusion and intercultural exchange. She has authored numerous publications on these topics.

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